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Energy Efficient Clustering-Based Mobile Routing Algorithm on WSNs

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ABSTRACT In this paper, we propose and discuss two types of algorithms to improve energy efficiency in Wireless Sensor Networks. An efficient approach for extending the life of a network is known as ''sensor clustering'' in wireless sensor networks. In proposed algorithms, the study area where sensor nodes are randomly distributed is divided into clusters. In each cluster, the sensor that is the closest to the cluster center and has the highest residual energy is chosen as the cluster head. To make this choice, a greedy approach and artificial neural network methods are applied. In addition, to reduce the energy consumption of cluster heads, a mobile sink is used. The list of routes to be used by the mobile sink is calculated with the genetic algorithm. According to the route information, the mobile sink moves to the clusters and initiates the data collection process for each cluster. We compared our models according to the round value at which all sensor nodes run out of energy and the energy consumption by the network per round. Simulation results show that the proposed models increase the energy efficiency and extend the network lifespan.

INDEX TERMS Energy efficiency, LEACH, wireless sensor network.

I. INTRODUCTION

Today, the development of sensor technologies allows the measured data to be transferred to the target area via wireless communications. The measured values are obtained as electrical signals and transmitted over long distances using wireless technologies [1], [2].

A network structure called the Wireless Sensor Network (WSN) is formed with the combination of hundreds of wireless detection devices called sensor nodes for a specific mission. The role of a sensor network is to detect and send environmental information to a central location called the base station (BS) or target node (TN) where the monitoring is performed [3], [4].

In WSN, most sensors operate with batteries as one of the sources of energy. In most cases, charging or replacing these batteries is not feasible [5], [6]. Data transfer in WSN is provided by high energy consumption. To collect the data for a long time and transmit data within the network [7], it is very important to solve the energy efficiency problem in WSNs [8].

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The clustering strategy for sensors is a method used to improve the energy efficiency of WSNs by balancing the consumption of energy [9]. In this configuration, the sensors are split into clusters according to the parameters defined [10], and one of the nodes in the cluster is selected as the cluster head (CH). CH nodes are responsible for collecting data from cluster members (CMs) and transmitting data to the BS or sink. It is difficult to choose the appropriate candidate among the nodes in the cluster to be the CH. CH consumes more energy because it receives data from the remaining nodes, collects the data, and sends the data collected to the BS or sink [11]. Because having the role of the CH is an energy-consuming process, a single node cannot continuously be in the CH role. Therefore, the replacement of CHs incorrect intervals is necessary [12], [13]. Figure 1 shows the cluster based WSN architecture.

In those scenarios where BS is stationary, the nodes close to the BS serve as relay nodes. Therefore, CHs close to the target consumes their energy much faster and create energy holes in the sensor network. Using BS mobility is considered to be an effective method to mitigate this problem [14]–[17].

The remainder of this paper is organized as follows. Section 2 reviews related work on clustering routing protocols to optimize the energy problem, while

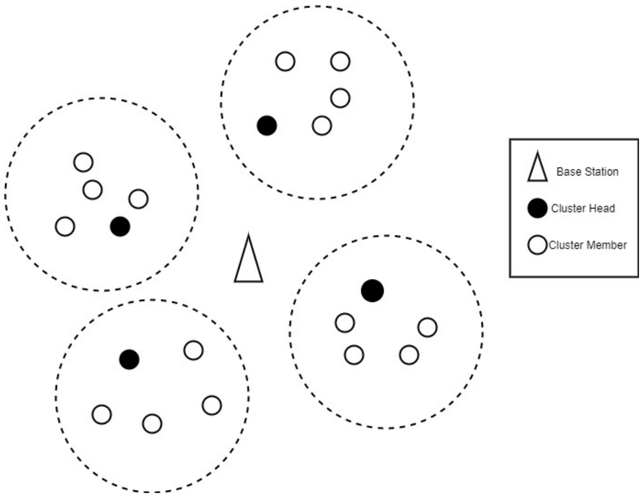

FIGURE 1. Cluster based WSN architecture.

Section 3 presents the models used and the CH selection method. Section 4 describes our proposed models, while Section 5 shows the performance evaluation and results. Finally, Section 6 presents the conclusions and discusses future work.

II. RELATED WORKS

The clustering strategy is a system aimed at improving the energy efficiency of WSNs by balancing the consumption of energy. This strategy organizes the nodes in separate clusters whose nodes are close together geographically and logically partitions the network topology into a hierarchical structure [18].

In general, the network has two types of roles: CH and CM. For an energy-constrained network, the clustering algorithm plays an important role in saving power. Choosing right CH will balance the load on the network, thereby reducing the consumption of energy and prolonging the network lifespan [2], [19].

The primary objective in the design of the routing algorithm for a WSN is to improve energy efficiency to extend network's. To achieve this goal, it is more important to direct data traffic to balances energy consumption in proportion to the current energy between nodes than to reduce the absolute energy consumed [20].

A classic protocol used for hierarchical data routing is the low-energy adaptive clustering hierarchy (LEACH) among clustering algorithms [21]. In this protocol, the network is grouped into clusters, and the sensor nodes whose role is CM transmit their data to the sensor node whose role is the CH. Each round, CH nodes are selected randomly by the protocol. CH nodes are responsible for collect detected data from CMs and transmit this data to BS or sink. The CH assigns time-division multiple access (TDMA) programs to the relevant CMs [22]. CMs are transmit their detected data over the allocated time period and reduce their energy consumption by switching between active and sleep status based on the time intervals allocated by CH. Only CHs can interact with the BS or the sink. Since the data is transmitted through CHs, CHs run out of energy in a short time [2]. Multi-hop communication can be useful in overcoming this issue, but it is still not effective on small networks [23].

TABLE 1. Table of abbreviations.

Abbreviations	Definition
ANN	Atrificial Neural Network
BCH	Backup Cluster Head
BLE	Bluetooth Low Energy
BS	Base Station
CG	Cluster Congregations
CH	Cluster Head
CM	Cluster Member
CSMA/CA	Carrier-Sense Multiple Access With Collision Avoidance
EA	Evolutionary Algorithm
EESRA	Energy-Efficient Scalable Routing Algorithm
GA	Genetic Algorithm
GPS	Global Positioning System
CG	Cluster Congregations
CH	Cluster Head
I-LEACH	IoT LEACH
LEACH	Low-Energy Adaptive Clustering Hierarchy
MS	Mobile Sink
MSPT	Mobile Sink Selective Path Priority Table
R-LEACH	Residual Energy Based LEACH
SCH	Second Cluster Head
T2FL	Type 2 Fuzzy Logic
TDMA	Time-Division Multiple Access
TN	Target Node
WSN	Wireless Sensor Network

It is difficult to choose a CH since many considerations must be taken into selection when choosing the best node in the cluster, such as the distance between nodes, the residual energy, the mobility, and the efficiency of each node [24]. The LEACH algorithm extends the network lifespan; however, it has many limitations. For example, the selection of CH is performed randomly. That is, low-energy nodes and high-energy nodes have the same probability of being chosen as the CH. Therefore, when a low-energy node is selected as a CH due to intensive processing, it can consume energy more quickly [25], [26].

In the literature, there are many studies on the LEACH protocol [20], [25], [27]–[30]. LEACH operates with a random CH selection in each round, and it is not possible to re-select the selected CH in the next round. Behera *et al.* [25] set a threshold value in their study to re-select CH for the next round. At the beginning of the tour, the residual energy of the CH selected is measured and compared with the threshold value. If it is greater than the threshold value, in the next round, the same node reselect as CH. However, IoT LEACH (I-LEACH) assumes single-hop communication. The distance between the CHs and BS can be large in large-scale WSNs, meaning high energy consumption in forwarding information to the BS. Thus, energy is consumed more quickly by CHs.

The Mobile Sink Selective Path Priority Table (MSPT) algorithm was proposed by Ogundile *et al.* [20], which aims to balance the energy consumption in WSNs, thereby maintaining the life and functionality of the network for a reasonable period time. CH selection is achieved in the first phase. In the second phase of the algorithm, nodes define an alternative path by selecting the two nodes closest to them within the cluster. Energy cost table calculation is made according to the total energy, the energy range, the energy ratio, and the energy percentage characteristics. The determined values are entered into the matrix in the third phase, and the route information with the minimum value is chosen. The major downside of this paper is that how the selection of the cluster and CH is determined is not stated.

In its proposed energy-efficient scalable routing algorithm (EESRA), Elsmany *et al.* [27] proposed a three-layer hierarchical structure to reduce the burden of CHs. In the setup phase, the random selection used in the LEACH protocol is applied to select the cluster. Clusters are formed after the CH selection. Each CH has the choice of one or more cluster congregations (CGs). In the steady-state phase, the CMs transmit the data they perceive to the CG using carrier-sense multiple access with collision avoidance (CSMA/CA). Finally, CG completes the tour by transmitting the collected data to the CH using TDMA. The results of the paper indicate that the proposed method improves the energy efficiency.

Sharma *et al.* [28] suggested energy-efficient clustering based on fuzzy c-means and differential evolution. The BS performs the clustering operation. The nodes are prevented from consuming energy for clustering in this way. By determining the optimum number of clusters in the network, a load-balanced cluster is generated with the fuzzy C means (FCM) algorithm. Each node can be selected as the best node CH according to the fitness value calculated by the Evolutionary Algorithm (EA). However, the network lifetime and functionality of a large-scale network are limited by single-hop communication used for data transmission and a fixed BS.

Behera *et al.* [29] proposed the residual energy-based LEACH (R-LEACH) protocol, which is a two-step hierarchical clustering algorithm. The goal of the proposed structure is to select the CH concerning important parameters, such as the initial energy, remaining energy of the individual node, and the optimum number of CHs in the network. The CHs and clusters are generated using the LEACH algorithm during the setup phase. The new CH is chosen at the end of the round based on the residual energy of the remaining nodes. Each node transmits its data to the CH in the steady-state phase during the allocated period. After all CMs in the cluster finish transferring data to CH, CH completes the tour by sending the received data to the BS with one or more hops. Intra-cluster distances can increase within large-scale WSNs. The energy consumption of the nodes in this situation can be rapid.

Lin and Wang [30] suggested a third role called the backup cluster head (BCH), in addition to the CH and CM roles. The node with the highest energy is chosen as the CH after the sensors in the network are clustered. The CH analyses in its cluster the energies of the CMs and then selects the node with the highest energy as the BCH. In TDMA time frames, the CH collects data from the CMs. The energy ratios between the CH and BCH are compared at the end of each round. In order to ensure energy efficiency, the node with the highest energy between CH and BCH is allocated as the new CH. However, the main drawback of this paper is that it does not report the network output of large-scale WSNs.

Yazici *et al.* [31] propose a fusion-based wireless multimedia sensor network (WMSN) framework that reduces the amount of data to be transmitted over the network by intra-node processing. In this study, to reduce the amount of information to be transmitted to the base station and extend the lifespan of WMSN, three different layers have been developed for detecting and classifying objects. Two-Tier Distributed Fuzzy Logic Based Protocol (TTDFP) is developed in the proposed framework for efficient aggregation of data in multi-hop wireless sensor networks to reduce the amount of information to be transmitted to the base station and extend the lifespan of WMSN.

Sert and Yazıcı [32] propose the utilization of a Modified Clonal Algorithm selection (CLONALGM) to improve the performance of rule-based fuzzy routing algorithms. The study takes an initially defined fuzzy output function and approximates it to the optimality based on the principles of the CLONALG-M algorithm. To evaluate the performance of the proposed approach, it is applied to the fuzzy routing mechanisms selected, and the results obtained are compared to performing the original methodologies. The obtained results reveal that CLONALG-M is an efficient approximation approach for fuzzy routing methodologies in wireless sensor networks.

A simple and effective energy-efficient structural clustering algorithm was proposed by Padmanaban and Muthukumarasamy [33] for environmental monitoring areas. CHs are selected according to the average communication distance and remaining energy. By rotating the CH role between nodes at appropriate intervals, the proposed algorithm significantly reduces energy consumption.

A cluster-based error tolerance technique using a genetic algorithm was proposed by Rajeswari and Neduncheliyan [34]. The network is clustered according to a distance-based clustering algorithm that saves energy. For each CH, a backup node is selected based on coverage and residual energy parameters using a genetic algorithm (GA).

In type 2 fuzzy logic (T2FL) model, Nayak and Vathasavai [35] proposed a fuzzy logic-based clustering algorithm. The entire sensor network is divided into levels in the proposed structure and an efficient CH node is selected at each level based on the T2FL model. Three fuzzy identifiers, such as remaining battery power, distance to the BS, and concentration, are discussed.

The mobile sensor node selects itself as the CH based on its remaining energy and mobility in the mobility-based clustering protocol proposed by Deng *et al.* [36]. In the TDMA schedule, each of the CM nodes are assigned a time frame for data transmission in ascending order. A sensor node transmits its sensed data during its time period in the steady-state phase. Furthermore, Zhang and Yan [37] suggested an energy-efficient central clustering method. This method uses a central control algorithm to build an improved CH set with less mobility and more energy.

The general problem that exists in the methods proposed in [33]–[37] is that the communication in single-hop data transmission limits the network lifespan of a large-scale network. In this paper, we propose a mobile routing algorithm with low energy and adaptive clustering hierarchy. For both intra- and inter-cluster communication, we use single-hop transmission in our model. Furthermore, we separate clusters from each other according to an optimal Bluetooth Low Energy (BLE) connection distance in constant intervals, and thus, we model a scalable WSN. In addition, to collect data from CHs, we use a mobile sink. Thus we reduce the energy consumption on the CH node by minimizing the distance between the CHs and the sink. Despite the changes in the network size, the proposed model offers a way to preserve the network lifetime. The proposed model against R_LEACH is evaluated in this paper in terms of energy efficiency with regard to changes in network size.

III. MODELS AND CLUSTER HEAD SELECTION

We aim to collect and analyze real-time data with agriculture 4.0 and increase product and operational efficiency with the actions to be taken. In this context, we offer energy-efficient clustering-based mobile routing algorithm in Mesh networks consisting of BLE Sensors to get better quality and more efficient products in the field with the right amount of irrigation, spraying, and fertilization at the right time by analyzing moisture, temperature, and mineral-like data in the soil.

In our energy-efficient clustering-based mobile routing study on wireless sensor networks consisting of BLE Sensors, we consider two different approaches. Each approach is composed of two phases. In the first phase, we generate the clusters and the MS route information. After defining the clusters and the MS path, the MS moves to the following clusters according to the route details and initiates the second phase. In the second phase, MS selects the appropriate CH. The CMs transfer the data they collect from the study area to CH in the data collection process. CH transmits the gathered data to the MS.

A. NETWORK MODEL

In our proposed model, we use BLE sensors that we assume are randomly distributed in a two-dimensional region, and their positions are constant during the network lifespan. The sensors have the same initial value, and for each sensor node, there is a Global Positioning System (GPS) sensor, and we ignore the energy consumption of the GPS sensor. Sensors share x and y coordinates and remaining energy information with MS. The energy usage is ignored while the sensors report position and energy data to the MS. The packet size is set to a fixed value, as in the simulation parameters. And, each round, the nodes convey only one message. The area is divided into sections by a mobile sink at 30 m2 intervals, and in each section, the sensors form a cluster. Within the cluster, according to the remaining energy and distance between nodes and cluster center, the CH and second cluster head (SCH) are selected by MS. The information obtained by the CMs is transferred to the CH, and data collected by the CH is transferred to the MS.

TABLE 2. Simulation parameters.

Symbol	Description	Value
A	Network size	60 m x 60 m , 120 m x 60 m, 90 m x 90 m , 150 m x 60 m
n	Total number of sensor nodes	200, 400, 800, 1000, 1600
E_0	Initial energy of nodes	2 J
E_{DA}	Energy dissipation: aggregation	5 nJ/bit
E_{amp}	Energy dissipation: power amplifier	10 pJ/bit
E_{elec}	Energy consumed to run the transmitter or the receiver circuit per bit	50 nJ/bit
k	*Data size of packet*	4000 bits

B. ENERGY MODEL

We use the "first-order radio" model to calculate the energy to be used to transfer k bit data to a point at a distance d and to receive k bit data from a point at a distance d as specified in Equation (3) and (4). E_{elec} refers to the energy consumption for k bit data during sending or receiving. E_{amp} is the transmission parameter, and the E_{DA} refers to the energy consumption for data aggregation. In our models, the parameter values used are as shown in Table 2.

C. CLUSTER HEAD SELECTION

In our proposed model, nodes within every 30 m^2 form a cluster as in shown Figure 2. In a cluster, nodes are evaluated by their distance from the cluster center and its residual energy. The node closest to the cluster center with the maximum residual energy is chosen as CH, and the second is chosen as SCH.

The distance between its position and its cluster center is determined for each sensor by the Euclidean distance defined as follows (1).

$$dist = \sqrt{(x_{node} - x_{center})^2 + (y_{node} - y_{center})^2} \tag{1}$$

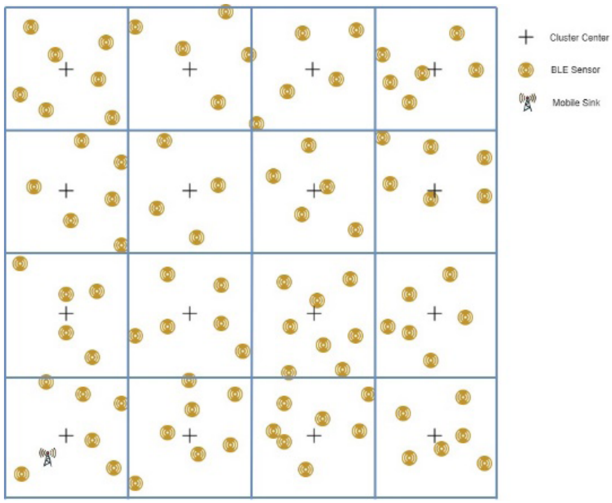

FIGURE 2. Clustering with 30 m2 intervals according to BLE communication distance.

Due to the broad range of measured distance values, by using min-max normalization to achieve more reliable results in the selection of the CH, we minimize the lengths based on the cluster to the range of [0,1].

$$n\_dist = \frac{dist_{node} - min_{dist}}{max_{dist} - min_{dist}} \tag{2}$$

In Eq(2), $dist_{node}$ is the distance between node and cluster center, min_{dist} is the value of the node at the minimum distance value from the cluster center, max_{dist} is the value of the node at the maximum distance from the cluster center.

Energy consumed by the CM to send k bit data through a distance d as:

$$E_{TX}(k, d) = \begin{cases} E_{elec} * k + E_{fs} * k * d^2; & d \leq d_0 \\ E_{elec} * k + E_{amp} * k * d^4; & d > d_0 \end{cases} \tag{3}$$

where E_{elec} is the energy consumption by the receiver or the transmitter per bit, k is the data size of the package, E_{amp} and E_{fs} are the amplifier parameters of transmission corresponding to the multi-path fading model and the free-space model, respectively. And d is the distance [25].

Energy consumption by the CH to receive the sent data as:

$$E_{RX}(k, d) = (E_{elec} + E_{DA}) * k \tag{4}$$

The transmission distance threshold d_0 is derived as:

$$d_0 = \sqrt{\frac{E_{fs}}{E_{amp}}} \tag{5}$$

where E_{DA} is the energy consumption for data aggregation [25].

The residual energy of the sensor node is:

$$E_{residual} = E_0 - E_{total} \tag{6}$$

where E_0 is the initial energy of the node and E_{total} is the energy consumed by the node [25].

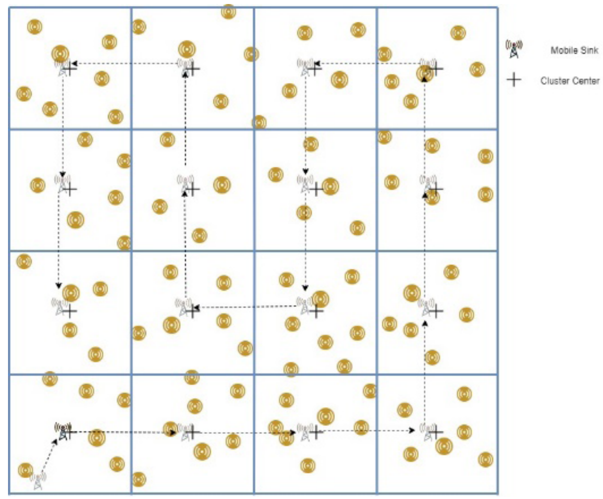

FIGURE 3. Creation of route for MS according to cluster centers.

According to the formula below, the node with the highest f value is determined as the CH, and the second-highest f value is selected as SCH.

$$f = (E_{residual} - n\_dist) \tag{7}$$

D. MOBILE ROUTING

After the clusters are generated, the route list is created by MS by using GA according to the cluster centers as shown in Figure 3. MS travels to the next cluster center according to this route list, and initiates the process of data collection.

IV. PROPOSED MODEL

In the energy-efficient cluster-based mobile routing study on BLE sensor networks, we discuss two different approaches. Each approach consists of two parts. Clustering, calculating the MS route and CH selection is performed in the first section. MS travels around the cluster centers according to the calculated route in the second part and initiates the process of data transfer for each cluster it reaches. CH assigns TDMA frames to the CMs in the data transmission process, and CMs transmit their data over the allotted time frame to the CH. CH transfers the collected data to the MS at the end of the process.

A. CLUSTERING WITH GREEDY APPROACH AND MOBILE ROUTING WITH GENETIC ALGORITHM (GREEDY&GA)

In phase one, sensors are randomly distributed to the relevant study area. By MS, the environment in which the sensor is distributed is clustered at 30 m^2 intervals, the center of each cluster is calculated, and there is information about which cluster each sensor is in. And, the route list to be used by MS is calculated with GA. After the genetic algorithm parameters are created, the initial population is generated. The fitness value is calculated for each chromosome in the population. New generations are created by applying selection, crossover, and mutation steps respectively until the optimization or stopping criterion is reached. New generations are added to the

TABLE 3. GREEDY&GA algorithm.

```
initialization of network and parameter
establishing of the clusters within 30 meter square
finding the cluster center and cluster members
compute cluster distances according to all possibilities and establish shortest mobile sink route with GA
while alive nodes > 0
    for each cluster in the mobile sink path
        compute the distance between cluster members and cluster center according to (1)
        compute residual energy of cluster members according to (6)
        min-max normalization for cluster according to (2)
        set the max value according to (7) as cluster head
        for each cluster member
            if node = cluster member
                compute energy consumption according to (3)
            else if node= cluster head
                compute energy consumption according to (4, 3)
            end if
            update residual energy
            if residual energy <= 0
                node is dead update the alive node
            end if
        end for
    end for
end while
```

population. When the stop criterion is reached, the chromosome with the best fitness value is selected. In the second phase, the Euclidean distance between each sensor in the cluster and the cluster center is calculated. After calculating the distances of all sensors in the cluster, min-max normalization is applied and distance values are drawn to the range of 0 to 1.

The sensor with the highest fitness value is selected as CH according to the results of the normalization and the residual energy. In BLE sensors, this structure corresponds to the Master mode. In addition, the node with the second highest fitness value is also kept in memory as SCH at the end of the round to allow comparisons. MS moves to the next cluster center according to the route list defined in phase one. CH generates a TDMA schedule dependent on the number of CM in the cluster and assigns charts to all CM's in the cluster where MS is located. On its own schedule, each node transfers the data they detect in the environment to CH. After the transfer, the sensors go into sleep mode. After transmission, the residual energies of the sensors are calculated. When the sensor runs out of energy, it is removed from the cluster. After MS traveling all the clusters on the route, the round ends. When the round is complete, CH is compared to the node with the SCH. If the new value of the previous round CH selected node is less than the new value of the SCH, the CH selection is repeated, and if not, the same sensor re-select as CH. The process is repeated beginning from phase two until there are no active sensors left in the network. Table 3 shows the algorithm of Greedy&GA. The big O notation of the model is O (n^5).

B. CLUSTERING WITH ARTIFICIAL NEURAL NETWORK AND MOBILE ROUTING WITH GENETIC ALGORITHM (ANN&GA)

Clustering, determining cluster centers, and creating mobile sink routes, which were carried out in the first phase, are also applied as in the same way in this approach.

The artificial neural network is trained with test input and test output data. Test input data contains the x and y coordinates and residual energy values of the sensors and the x and y coordinates of the cluster centers. Test output data includes the fitness value according to the input data calculated by the greedy method. In the second phase, by entering the x and y coordinates and the residual energies of the sensors in the cluster and the x and y coordinates of the cluster center, the artificial neural network is operated. The sensor with the highest output value is selected as CH. In BLE sensors, this structure corresponds to the Master mode. In the continuation of the algorithm, according to the route list created in phase one, MS moves to the next cluster center. And performs the data gathering steps described in a Greedy&GA approach. Table 4 shows the algorithm of ANN&GA. The big O notation of the model is O (n^5).

V. PERFORMANCE EVALUATION AND RESULT

Our recommended models for energy consumption evaluation have been compared to R-LEACH. We focused on assessing the energy efficiency, considering five scalability case studies with 200 nodes in 60m $\times$ 60m area, 400 nodes in 90m $\times$ 60m area, 800 nodes in 90m $\times$ 90m area, 1000 nodes in 150m $\times$ 60m area and 1600 node in 150m $\times$ 60m area. We compared our study to the R-LEACH algorithm by the number of rounds where all nodes on the network are depleted, first node depleted, half of nodes depleted, and the energy consumption of the network per round condition. We ran our study 100 times with the simulation parameters which are shown in Table 2.

BLE sensor nodes are randomly distributed for each case study. In order to make the correct comparison, the same sensor set was used for all three models in each case study. The mobile sink position is fixed at 20 m $\times$ 20 m with unlimited energy. All nodes are started with 2J initial energy. In this study, the packet size was considered 4000 bits. And simulation is conducted using MATLAB(MathWorks, Natick,MA,USA).

We present the simulation results of the proposed Greedy&GA and ANN&GA in comparison with the R-LEACH protocol using the same simulation parameters as in Table 5. The models were evaluated via the number of rounds where all nodes on the network are depleted.

TABLE 4. ANN&GA algorithm.

```
1:  initialization of network and parameter
2:  establishing of the clusters within 30 meter square
3:  finding the cluster center and cluster members
4:  compute cluster distances according to all
possibilities and establish shortest mobile sink route
with GA
5:  generate test input data from the x and y
coordinates of the nodes and the cluster center
6:  generate test target data from fitness function
according to test input data
7:  train the neural network with test input and test
target data
8:  while alive nodes > 0
9:      for each cluster in the mobile sink path
10:         run the trained network for cluster
11:         set the max value in output as a cluster head
12:         for each cluster member
13:             if node = cluster member
14:                 compute energy consumption
according to (3)
15:             else if node= cluster head
16:                 compute energy consumption
according to (4, 3)
17:             end if
18:             update residual energy
19:             if residual energy <= 0
20:                 node is dead update the alive node
21:             end if
22:         end for
23:     end for
24: end while
```

TABLE 5. Comparison of R_LEACH, GREEDY&GA, and ANN&GA.

Area	Node Number	Protocol	AND	FND	HND
60m x 60m	200	R-LEACH	4428	1432	2110
		Greedy&GA	5919	2718	4934
		ANN&GA	8404	140	5121
90m x 60m	400	R-LEACH	4634	1518	1834
		Greedy&GA	6203	2743	4935
		ANN&GA	8547	106	5383
90m x 90m	800	R-LEACH	4213	2056	2183
		Greedy&GA	5922	2632	4889
		ANN&GA	8945	86	4862
150m x 60m	1000	R-LEACH	4086	2269	3080
		Greedy&GA	6022	2473	4793
		ANN&GA	8643	69	5164
150m x 60m	1600	R-LEACH	4293	2010	3034
		Greedy&GA	5991	2574	4820
		ANN&GA	8817	47	5357

The number of rounds refers to the situation that the MS travels to the cluster center where it started by completing the data collection process from the CH by using all clusters in line with the route drawn. With the increase in the number of rounds, the sensors deplete their energy and become passive. When the comparison results are examined, it is seen that the CH selection with Greedy&GA and ANN&GA models gives better results by increasing the number of rounds. As the number of sensors increases, the number of elements in the cluster also increases. More sensor nodes in the cluster means that the CH node consumes more energy. Therefore, as the number of sensors increases in the cluster, a decrease in the total number of laps is observed as in the 1000 node 150m x 60m area and 1600 node 150m x 60m area case study.

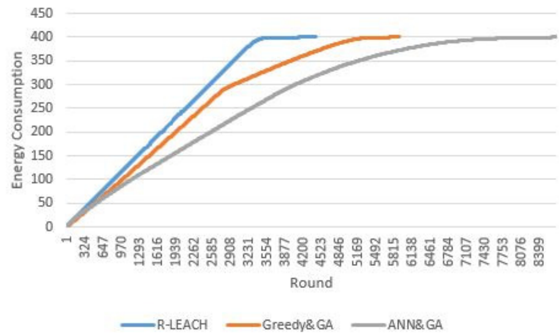

FIGURE 4. Energy consumption of network for 60m × 60m 200 nodes.

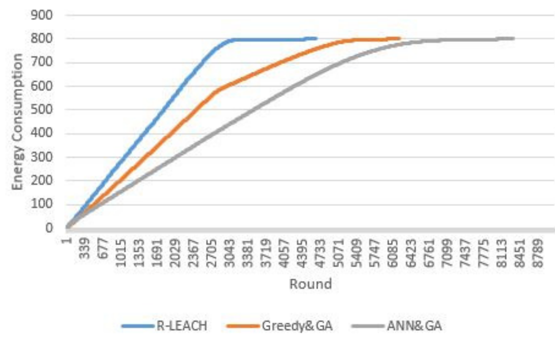

FIGURE 5. Energy consumption of network for 120m × 60m 400 nodes.

In the evaluation carried out based on energy consumption, our models were compared to the R-LEACH protocol. In the R-LEACH protocol, CH selection is made according to the remaining energy of the nodes and a node selected as CH cannot be selected again in the next round. In terms of energy consumption and its effect on the lifetime of the network, the downside of the R-LEACH protocol is that, even if the residual energy is high, R-LEACH allows a sensor node to become CH that is far from the. Unlike R-LEACH, our models use the distance parameter to the cluster center in CH selection. In addition, unlike the R-LEACH protocol, at the end of the tour, a comparison is made according to the fitness value between CH and SCH. As long as the fitness value of the CH is higher than SCH, the same sensor node reselects as CH. In the proposed models, CH selection aims to find the node closest to the center and with the highest residual energy.

There is a comparison of energy consumption depending on the scenarios applied in Figure 4 to Figure 8. It is seen that CH selection based on the fitness value found by running Greedy&GA and ANN&GA consumes less energy than R-LEACH and extends the network lifespan. There are two factors that reduce the energy spent here. The first one is the

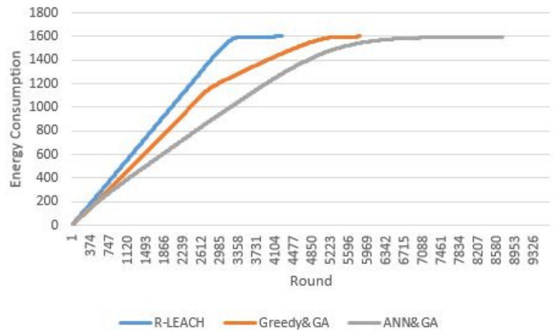

FIGURE 6. Energy consumption of network for 90m × 90m 800 nodes.

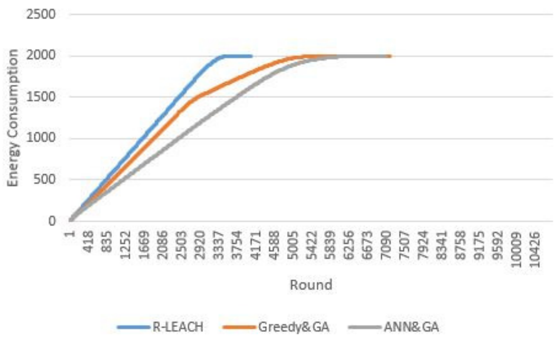

FIGURE 7. Energy consumption of network for 150m × 60m 1000 nodes.

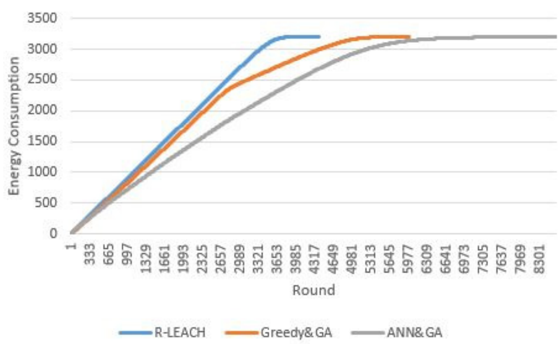

FIGURE 8. Energy consumption of network for 150m × 60m 1600 nodes.

addition of the closeness calculation to the cluster center, as is different from R-LEACH in the CH election. The second one is the use of the mobile sink. The use of MS reduces the distance between CH and the sink for data transmission and reduces energy consumption by preventing multiple hops. In addition, when the results are evaluated, it is seen that the energy consumption is associated with the total number of rounds during the network lifespan. Besides, when we look at the comparison between the models themselves, it is seen that the ANN model is more successful in energy consumption and the lifespan of the network.

From the above analysis, it is clear that proposed models show better performance for both small and large areas with scarcely as well as densely populated networks.

VI. CONCLUSION AND FUTURE WORKS

One of the strategies used to balance the energy consumption and improve the energy efficiency of WSNs is the technique of clustering sensor nodes. According to this technique, one of the sensor nodes is selected as CH within the cluster. The task of this node is to collect data from the CMs in the cluster where it is located and transmit it to sink. Choosing the correct node for CH between nodes and replacing the selected node at the right intervals is a critical process for each cluster. In scenarios where the sink is fixed, nodes close to the sink act as a relay node. That's why near-target CH's consume their energy much faster and creating energy holes in the sensor node network. Using a mobile sink is an effective way to ease this problem.

In this paper, we proposed two different, energy efficient clustering based mobile routing algorithms based on the LEACH protocol. The study area where sensor nodes are randomly distributed is divided into clusters at intervals of 30 m^2. In each cluster, we use two different approaches for CH selection by greedy algorithm and ANN. With the GA, the shortest path drawing between the mobile sink and the cluster centers was realized. The mobile sink was moved to the clusters using that route and collected the data.

We evaluated our study according to AND, FND, HND, and energy consumed metrics. When statistical results were evaluated according to AND and HND metrics, we observed the ANN&GA gave the best result, and the Greedy&GA have a better result than the R-LEACH and maintain the number of active nodes for a longer time during the network lifespan. Although the statistical data on the FND metric revealed that the first node consumed faster energy in the ANN&GA, it gave better results in the HND and AND metrics than the other models.

As a result of the clusters formed at 30 m2 intervals, the selection of CH depending on the residual energy and distance from cluster center and using mobile sink, simulation results clearly show that the energy consumed by the network is reduced and extending the network lifespan much more than R-LEACH with using Greedy&GA and ANN&GA models.

For future works, we will be carried out by working on different algorithms and network sizes for the scalability of the algorithm and we will include the energy spent by the MS and the energies that the sensor nodes spend for the CH connection in our models. In this way, we can measure the effectiveness of the methods used in the models on the life span of the network better.

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