An energy aware fuzzy approach to unequal clustering in wireless sensor networks

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ABSTRACT

In order to gather information more efficiently in terms of energy consumption, wireless sensor networks (WSNs) are partitioned into clusters. In clustered WSNs, each sensor node sends its collected data to the head of the cluster that it belongs to. The cluster-heads are responsible for aggregating the collected data and forwarding it to the base station through other cluster-heads in the network. This leads to a situation known as the hot spots problem where cluster-heads that are closer to the base station tend to die earlier because of the heavy traffic they relay. In order to solve this problem, unequal clustering algorithms generate clusters of different sizes. In WSNs that are clustered with unequal clustering, the clusters close to the base station have smaller sizes than clusters far from the base station. In this paper, a fuzzy energy-aware unequal clustering algorithm (EAUCF), that addresses the hot spots problem, is introduced. EAUCF aims to decrease the intra-cluster work of the cluster-heads that are either close to the base station or have low remaining battery power. A fuzzy logic approach is adopted in order to handle uncertainties in cluster-head radius estimation. The proposed algorithm is compared with some popular clustering algorithms in the literature, namely Low Energy Adaptive Clustering Hierarchy, Cluster-Head Election Mechanism using Fuzzy Logic and Energy-Efficient Unequal Clustering. The experiment results show that EAUCF performs better than the other algorithms in terms of first node dies, half of the nodes alive and energy-efficiency metrics in all scenarios. Therefore, EAUCF is a stable and energy-efficient clustering algorithm to be utilized in any WSN application.

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1. Introduction

There have been recent advances in micro-electro-mechanical systems (MEMS) technology, wireless communications, and digital electronics. These advances have enabled the development of low-cost, low-power, multifunctional nodes which are small in size and which communicate with each other using radio frequencies [1]. A single sensor node has limited capability in sensing and it is only capable of collecting data from a limited region within its range. Therefore, in order to gather useful information from an entire of WSN, the data must be collected through the collective work of a number of sensor nodes. These collaboratively working sensor nodes form a wireless sensor network (WSN).

In WSNs, each sensor node receives a signal from a limited region. This signal is processed in that sensor node and the sensed data is generally transmitted to the observers (e.g. base stations). Sensor nodes consume energy while receiving, processing and transmitting data. In most of the cases, these sensor nodes are equipped with batteries which are not rechargeable. Therefore, energy efficiency is still a major design goal in WSNs [2].

In order to aggregate data through efficient network organization, nodes can be partitioned into a number of small groups, called clusters [2]. In general, each cluster has a cluster-head which coordinates the data gathering and aggregation process in a particular cluster. Clustering in WSNs guarantees basic performance achievement with a large number of sensor nodes [3,4]. In other words, clustering improves the scalability of WSNs [5]. This is because clustering minimizes the need for central organization and promotes local decisions.

There has been a substantial amount of research on clustering protocols for WSNs. Most of the clustering protocols utilize two techniques, selecting cluster-heads with more residual energy and rotating cluster-heads periodically to balance energy consumption of the sensor nodes over the network [6]. These clustering algorithms do not take the location of the base station into consideration. This lack of consideration causes the hot spots problem in multi-hop WSNs. The cluster-heads near the base station tend to die earlier, because they are in a heavier relay traffic than the cluster-heads which are located relatively far from the base station. In order to avoid this problem, some unequal clustering algorithms have been proposed in the literature [6,7]. In unequal clustering,

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the network is partitioned into clusters of different sizes. The clusters close to the base station are smaller than the clusters far from the base station.

In this paper, a fuzzy energy-aware unequal clustering algorithm (EAUCF) is introduced to make a further improvement in maximizing the lifetime of the WSN. EAUCF is a distributed competitive algorithm which selects the cluster-heads via energy-based competition among the tentative cluster-heads selected using a probabilistic model. EAUCF mostly focuses on assigning appropriate competition ranges to the tentative cluster-heads. In order to make wise decisions, the proposed approach uses the residual energy and the distance to the base station of the sensor nodes. In addition to this, EAUCF employs fuzzy logic to handle uncertainties in competition radius estimation.

There are several proposed clustering algorithms in the literature. The Low Energy Adaptive Clustering Hierarchy (LEACH) [8] protocol rotates the cluster-heads periodically in order to balance energy consumption. Cluster-heads are rotated in each round. The term *round* refers to the interval between two consecutive cluster formation process. LEACH uses a pure probabilistic model to select cluster-heads. Cluster-Head Election Mechanism using Fuzzy Logic (CHEF) [9], Energy-Efficient Unequal Clustering (EEUC) [6] and EAUCF also utilize randomized periodical rotation. However, they do not use a pure probabilistic model to select the final cluster-heads. EAUCF, CHEF and the approach of Gupta et al. [10] utilize fuzzy logic for handling uncertainties in clustering. CHEF and the approach of Gupta et al. assign chance values to the sensor nodes using the results inferred from predefined fuzzy if-then mapping rules. These chance values are used in cluster-head competition. However, EAUCF employs fuzzy logic for wisely adjusting the competition ranges of the tentative cluster-heads. EAUCF is an unequal clustering algorithm like EEUC. EEUC assigns unequal competition ranges to the tentative cluster-heads considering only the distance to the base station. In contrast, EAUCF employs both the residual energy and the distance to the base station of the tentative cluster-heads for estimating competition radius.

In order to evaluate the proposed algorithm, its performance is compared with that of some popular clustering algorithms in the literature, namely LEACH, CHEF and EEUC. The experiments are performed on four different predefined scenarios. The experimentation results show that EAUCF performs better than all of the other algorithms in all of the scenarios. Therefore, EAUCF is a stable and energy-efficient clustering algorithm that can be used in any WSN application.

The rest of this paper is organized as follows. In the next section, the research related to the proposed approach is briefly explained. In Section 3, the proposed clustering algorithm EAUCF is explained in detail. In Section 4, in order to evaluate EAUCF, it is compared with LEACH, CHEF and EEUC by using the simulation method and the detailed evaluation results are given. Finally, the paper is concluded and some possible future works are listed.

2. Related work

In the literature, a number of clustering algorithms have been proposed for WSNs. In this part, the key features of the most popular and recent clustering algorithms are explained.

LEACH is a distributed algorithm which makes local decisions to elect cluster-heads. If the cluster-heads that are selected do not change throughout the network's lifetime, then it is obvious that these static cluster-heads die earlier than the ordinary nodes. Therefore, LEACH includes randomized rotation of cluster-head locations to evenly distribute the energy dissipation over

the network [8]. LEACH also performs local data compression in cluster-heads to decrease the amount of data that is forwarded to the base station.

In the HEED (Hybrid Energy-Efficient Distributed Clustering) protocol, the residual energy of each sensor node is the primary parameter for probabilistic election of cluster-heads [2]. In case of a tie in cluster-head election, node degree or average distance to neighbors is used to determine the cluster-head. Experimentations that have been employed to evaluate the HEED protocol show that clustering and data aggregation at least double the lifetime of the WSN.

Kuhn et al. study the initializing of newly deployed ad hoc and sensor networks, and propose a probabilistic cluster-head election algorithm. In this approach, the probability of each node depends on the node degree [15]. This algorithm tries to find a dominating set of nodes which will be assigned as cluster-heads.

Ali et al. proposed a multi-objective solution by using a multi-objective particle swarm optimization (MOPSO) algorithm [11]. This algorithm aims to optimize the number of clusters in an ad hoc network as well as the energy consumption in nodes in order to provide an energy-efficient solution and reduce the network traffic. In this approach, inter-cluster and intra-cluster traffic is managed by the cluster-heads. The parameters that are considered by this algorithm are degree of nodes, transmission power, and the battery power consumption of the mobile nodes.

Some of the clustering algorithms employ fuzzy logic to handle uncertainties in WSNs. Basically, fuzzy clustering algorithms use fuzzy logic for blending different clustering parameters to elect cluster-heads. In the fuzzy clustering approach proposed by Gupta et al., the cluster-heads are elected at the base station. In every round, each sensor node forwards its clustering information to the base station. There are three fuzzy descriptors which are considered by the base station during cluster-head election. These fuzzy descriptors are node concentration, residual energy in each node and node centrality [10].

CHEF is a similar approach to that of Gupta et al. [10], but it performs cluster-head election in a distributed manner. Thus, the base station does not need to collect clustering information from all sensor nodes [9]. There are two fuzzy descriptors that are employed in cluster-head election. These are the residual energy of each node and local distance. Local distance is the total distance between the tentative cluster-head and the nodes within a predefined constant competition radius.

The sensor nodes closer to the base station consume more energy, because the network traffic increases as it approaches the base station [2]. Therefore, the nodes closer to the base station quickly run out of battery. In order to balance energy consumption over the network, unequal clustering approach is introduced. This approach is based on the idea of decreasing the cluster sizes as they approach the base station. If a cluster-head closer to the base station has less intra-cluster work, then it can contribute more to inter-cluster data forwarding. Shu et al. proposed an approach that aims to achieve optimal power allocation over the sensor network. This approach assigns larger cluster sizes to cluster-heads that take less role in data forwarding process. The proposed network model in this approach assumes a circular sensing region. However, generally sensor nodes are deployed randomly by throwing them at the target region. Therefore, this approach is not practical for real environments in most cases.

EEUC is a distributed competitive unequal clustering algorithm where cluster-heads are elected by local competition [9]. Every node has a preassigned competitive radius. This radius gets smaller as the nodes approach the base station. This makes EEUC an unequal clustering algorithm. The EEUC algorithm is also a probabilistic clustering algorithm, because in each cluster formation round it probabilistically decides whether it is going to participate to the
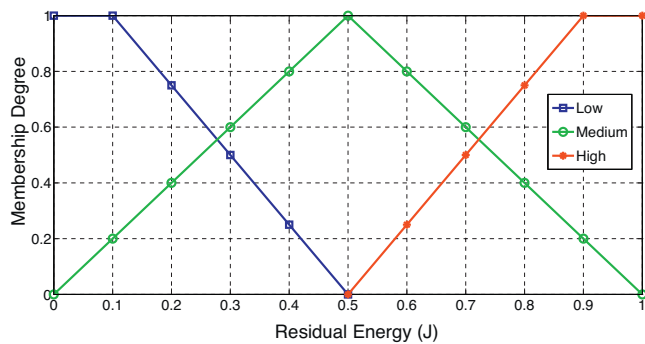
cluster-head election competition. If a sensor node has decided to participate in the competition, then it becomes a tentative cluster-head. Tentative cluster-heads in local regions compete in order to become actual cluster-heads. This competition is based on the residual energy of each tentative cluster-head.

3. Preliminaries

Before describing the proposed algorithm in detail, the characteristics of the system model that are used in the implementation are introduced. First, the assumptions that are made about the network model are listed:

- Sensor nodes are deployed randomly.
- All sensor nodes and the base station are stationary after the deployment phase.
- Nodes are capable of adjusting the transmission power according to the distance of the receiver nodes.
- The distance between nodes can be computed based on the received signal strength. Therefore, there is no need for sensor nodes to know their exact locations.
- All sensor nodes have the same amount of energy when they are initially deployed.
- The base station need not be located far away from the sensing region.
- All sensor nodes are identical.

The first order radio model that is employed in [8] is used for the energy dissipation model in simulations. Eq. (1) represents the amount of energy consumed in transmitting l bits of data to d distance. E_{elec} is the energy consumption per bit in the transmitter and receiver circuitry. ϵ_{amp} is the energy dissipated per bit in the RF amplifier.

$$E_{Tx}(l, d) = lE_{elec} + l\epsilon_{amp}d^2 \tag{1}$$

Eq. (2) represents the amount of energy consumed in receiving l bits of data.

$$E_{Rx}(l) = lE_{elec} \tag{2}$$

4. EAUCF clustering algorithm

In this section, the proposed clustering algorithm EAUCF (Energy-Aware Unequal Clustering with Fuzzy) is described in detail. The preliminary version of this study is included in [12]. EAUCF is a distributed competitive unequal clustering algorithm. It makes local decisions for determining competition radius and electing cluster-heads. In order to estimate the competition radius for tentative cluster-heads, EAUCF employs both residual energy and distance to the base station parameters. Moreover, EAUCF takes advantage of fuzzy logic to calculate competition radius. EAUCF is also based on a probabilistic model which is employed for electing tentative cluster-heads. However, it does not elect the final

Table 1
Fuzzy if-then mapping rules for competition radius calculation in EAUCF.

Distance to base	Residual energy	Competition radius
Close	Low	Very small
Close	Medium	Small
Close	High	Rather small
Medium	Low	Medium small
Medium	Medium	Medium
Medium	High	Medium large
Far	Low	Rather large
Far	Medium	Large
Far	High	Very large

cluster-heads just by depending on this model. The main flow of EAUCF is explained in Algorithm 1. R_{comp} and $resEnergy$ represent the competition radius and the residual energy of a particular sensor node, respectively.

Algorithm 1. Clustering algorithm of EAUCF protocol

```
1:    T ← probability to become a tentative cluster-head
2:    nodeState ← CLUSTERMEMBER
3:    clusterMembers ← empty
4:    myClusterHead ← this
5:    beTentativeHead ← TRUE
6:    μ ← rand(0,1)
7:    if μ < T then
8:        Calculate R_comp using fuzzy if-then mapping rules
9:        CandidateCHMessage(ID, R_comp, resEnergy)
10:       On receiving CandidateCHMessage from node N
11:       if this.resEnergy < N.resEnergy then
12:           beTentativeHead ← FALSE
13:           Advertise QuitElectionMessage(ID)
14:       end if
15:    end if
16:    if beTentativeHead = TRUE then
17:        Advertise CHMessage(ID)
18:        nodeState ← CLUSTERHEAD
19:        On receiving JoinCHMessage(ID) from node N
20:        add N to the clusterMembers list
21:        EXIT
22:    else
23:        On receiving all CHMessages
24:        myClusterHead ← the closest cluster-head
25:        Send JoinCHMessage(ID) to the closest cluster-head
26:        EXIT
27:    end if
```

In every clustering round, each sensor node generates a random number between 0 and 1. If the random number for a particular node is smaller than the predefined threshold T, which is the percentage of the desired tentative cluster-heads, then that sensor node becomes a tentative cluster-head. The competition radius of each tentative cluster-head changes dynamically in EAUCF, because EAUCF uses residual energy and distance to the base station to calculate competition radius. It is logical to decrease the service area of a cluster-head while its residual energy is decreasing. If the competition radius does not change as the residual energy decreases, the sensor node runs out of battery power rapidly. EAUCF takes this situation into consideration and decreases the competition radius of each tentative cluster-head as its battery power decreases. Radius computation is accomplished by using predefined fuzzy if-then mapping rules to handle the uncertainty. These fuzzy if-then mapping rules are given in Table 1. In order to evaluate the rules, the Mamdani Method [13], which is one of the most frequently used methods [10], is used as a fuzzy inference technique. The center of area (COA) method is utilized for defuzzification of the competition radius.

In order to calculate cluster-head competition radius, two fuzzy input variables are used. The first one is the distance to the base station. The fuzzy set that describes the distance to base station input variable is depicted in Fig. 1. The linguistic variables for this fuzzy set are *close*, *medium* and *far*. A trapezoidal membership function is chosen for *close* and *far*. On the other hand, the membership function of *medium* is a triangular membership function.

The second fuzzy input variable is the residual energy of the tentative cluster-head. The fuzzy set that describes the residual energy input variable is illustrated in Fig. 2. *Low*, *medium* and *high* are the linguistic variables of this fuzzy set. The *low* and *high* linguistic variables have a trapezoidal membership function while *medium* has a triangular membership function. A number of candidate membership functions are tested to find the best fitting functions for input variables. Finally, these membership functions are chosen, because they yield better results in the tests.

The only fuzzy output variable is the competition radius of the tentative cluster-head. The fuzzy set for competition radius is

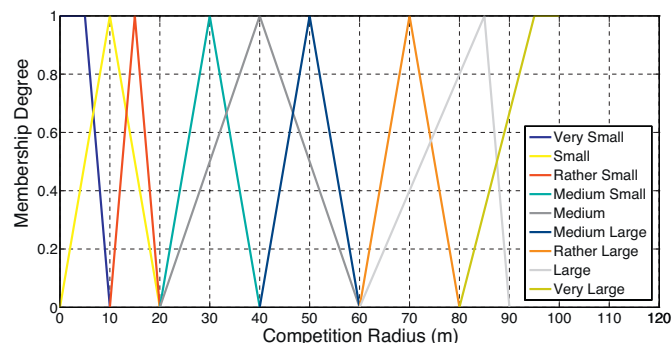**Fig. 1.** Fuzzy set for fuzzy input variable *DistanceToBase*.

Fig. 2. Fuzzy set for fuzzy input variable *ResidualEnergy*.

Table 2
Examples for fuzzy cluster competition radius calculation.

Example no	Distance (m)	Energy (J)	Radius (m)
1	112.90	1.0	45.31
2	20.12	1.0	20.61
3	65.92	1.0	31.61
4	84.31	0.999	38.88
5	84.31	0.70	33.47
6	103.77	0.50	36.65
7	122.80	0.64	46.02
8	112.89	0.59	41.08
9	99.30	0.29	34.63
10	8.94	0.76	12.46

of this parameter. The maximum distance to the base station is also a static parameter, because it is assumed that the sensor nodes are stationary. Each sensor node can determine its relative position to the base station considering the maximum distance to the base station in the WSN.

The change of competition radius according to residual energy and distance to the base station is demonstrated by the examples in Table 2. In these examples, the maximum distance to base station is 127 m and the maximum competition radius is set at 60 m. In examples 1, 2 and 3, the residual energy levels of the nodes are identical and equal to 1 J. However, their distances to the base station are different. As it approaches the base station, the competition radius of the sensor node decreases. In examples 4 and 5, the distance to the base station is identical, but energy levels are different. The node which has lower energy has a lower competition radius.

After each tentative cluster-head determines its competition radius, cluster-head competition begins. Each tentative cluster-head advertises *CandidateCH Message* to compete with other tentative cluster-heads locally. This message is advertised to the tentative cluster-heads which are inside the maximum cluster-head competition radius. It includes node ID, competition radius and the residual energy level of the source node. Residual energy is the key parameter in cluster-head competition. If a tentative cluster-head receives a *CandidateCHMessage* from another tentative cluster-head which is in its competition range and the residual energy of the source node is greater than the residual energy of the receiving node, then the receiving node quits the cluster-head competition and broadcasts a *QuitElectionMessage*. If a particular tentative cluster-head has the highest residual energy level among the tentative cluster-heads which it receives a *CandidateCHMessage* from, then it becomes a cluster-head. This competition guarantees that no other cluster-head exists in the competition radius of a particular cluster-head. After cluster-head election is completed, each ordinary sensor node joins the closest cluster, as in LEACH, CHEF and EEUC. Fig. 4 illustrates a WSN which is clustered by using the EAUCF algorithm. In this example, the number of deployed sensors is 200.

demonstrated in Fig. 3. There are 9 linguistic variables which are *very small*, *small*, *rather small*, *medium small*, *medium*, *medium large*, *rather large*, *large* and *very large*, *very small* and *very large* have a trapezoidal membership function. The remaining linguistic variables are represented by using triangular membership functions. The function in Fig. 3 is not a symmetric triangular function as in Figs. 1 and 2. This is because the function in Fig. 3 has provided better results in the experimentations.

If a particular tentative cluster-head's battery is full and it is located at the maximum distance to the base station, then it has the maximum competition radius. On the contrary, if a particular cluster-head's battery is near empty and it is the closest node to the base station, then it has the minimum competition radius. The remaining intermediate possibilities fall between these two extreme cases.

The maximum competition radius is a static parameter for a particular WSN. The base station broadcasts the value of this parameter to the entire network. Thus, all the sensor nodes know the maximum competition radius, in advance. Each of the sensor nodes can calculate their relative competition radius according to the value

5. Simulation results

In this section, the results of the experiments that are employed to evaluate EAUCF are presented. EAUCF is compared with three different clustering algorithms, namely LEACH, CHEF and EEUC. A WSN clustering simulator is implemented to evaluate the proposed algorithm. This simulation tool is able to simulate LEACH, CHEF, EEUC and EAUCF for different WSN configurations. Several experiments are conducted on this tool to evaluate the algorithm. Experimental results show that the proposed algorithm performs better than LEACH, CHEF and EEUC in all of the scenarios.

Handy et al. used the metrics *first node dies* (FND), *half of the nodes alive* (HNA) and *last node dies* (LND) in [14] to estimate the lifetime of the WSNs. FND denotes an estimated value for the round in
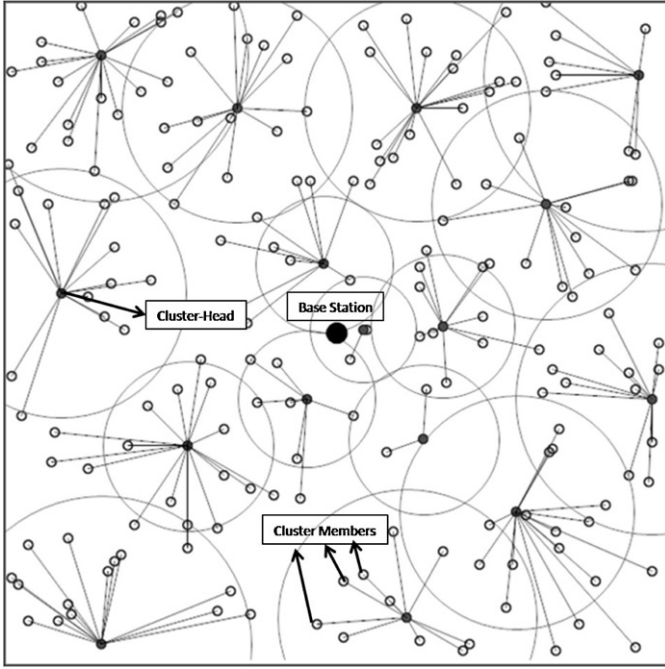

Fig. 3. Fuzzy set for fuzzy output variable *CompetitionRadius*.

Fig. 4. A WSN which is clustered by using EAUCF algorithm.

Table 3
Configuration of Scenario 1.

Parameter	Value
Network size	200×200 m
Base station location	$(100, 100)$ m
Number of sensor nodes	100
Initial energy	1 J
Data packet size	4000 bits
ϵ_{amp}	100 pJ/bit/m^2
E_{elec}	50 nJ/bit
Aggregation ratio	10%

to 2.5 as in the original study [9]. The optimal threshold P_{opt} for CHEF is calculated as approximately 0.3 for 100 nodes and 0.21 for 200 nodes using Eqs. (4) and (5) which are defined in [9]. Since the threshold T is set to 0.4 and the coefficient c is set to 0.5 for the EEUC clustering algorithm in [6], these values are also used in the experiments in this paper. In order to find an optimal threshold T value for EAUCF, several candidate threshold values are tried. Finally, this value is selected as 0.3, because it gives better results than other alternatives.

$$P_{opt} = \alpha \cdot P \tag{4}$$

$$P = \frac{\sqrt{n}}{\sqrt{2\pi}} \cdot \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \cdot \frac{\sqrt{A}}{(0.765 \times \sqrt{A} \times 0.5)^2} \cdot \frac{1}{n} \tag{5}$$

In order to produce more reliable results, every scenario is simulated 50 times, and the average of the results is taken.

5.1. Scenario 1

In this scenario, the base station is located at the center of the wireless sensor network. Each cluster-head forwards the aggregated data to the base station directly without using a relay node. The detailed configuration of this scenario is depicted in Table 3.

The maximum competition radius is assigned as 30 and 60 m for EEUC and EAUCF, respectively. These are the optimal maximum competition radius values for this scenario. After the wireless sensor network is deployed, the maximum distance to the base station is calculated as approximately 127.35 m. Table 4 shows the simulation results of this scenario.

As seen in Table 4, the proposed algorithm EAUCF performs better than LEACH, CHEF and EEUC for both FND and HNA metrics. The performances of CHEF and EEUC are close to each other, but CHEF performs slightly better than EEUC especially for FND. LEACH has the poorest performance among the four clustering algorithms for this scenario. EAUCF is 36.0% more efficient than LEACH, 10.7% more efficient than CHEF and 14.9% more efficient than EEUC if the FND metric is considered. It performs 30.7% better than LEACH, 4.9% better than CHEF and 6.4% better than EEUC if the HNA metric is used for performance evaluation.

The LEACH performance is the poorest, because it does not consider the residual energy level of the sensor nodes during clustering. It uses a pure probabilistic model for clustering, but this model itself is not sufficient to obtain the best solution. Since CHEF takes both energy and local distance parameters into consideration, it performs better than LEACH. EEUC also considers energy and distance to the base station. Hence, it has a better performance than LEACH.

which the first node dies. This metric is useful in sparsely deployed WSNs. However, in densely deployed WSNs, the death of a single node is not an important issue. Therefore, Handy et al. propose the metric HNA which denotes an estimated value for the round in which half of the nodes die. In addition to this, they provide another metric LND which denotes an estimated value for the overall lifetime of the network. However, LND is not a very useful metric, because after half of the sensor nodes die, the WSN becomes almost useless in most cases. Therefore, FND and HNA metrics are chosen to evaluate the performance of the algorithms.

In order to evaluate the proposed algorithm, four different scenarios are developed. In the first three scenarios, the base station is located at the center of the WSN. In the last scenario, the base station is outside the WSN.

In each round of the scenarios, first the cluster-heads are elected and then clusters are formed. Afterwards, each ordinary sensor node transmits 4000 bits of data to its cluster-head. Each cluster-head aggregates the received data with a certain aggregation ratio and forwards it to the base station. The aggregation ratio is set to 10% in the simulations. In the simulations of CHEF, Kim et al. also used the same aggregation ratio [9]. The length of the aggregated data for a particular cluster-head is calculated using Eq. (3).

$$L_{agg} = L_{rec} + (L_{rec} \times R_{agg} \times N) \tag{3}$$

In Eq. (3), L_{agg} represents the length of the aggregated data in bits while L_{rec} represents the length of the received data from each cluster member. R_{agg} is the ratio of aggregation and N is the total number of cluster members. For example, if a particular cluster has 20 cluster members each transmitting 100 bits of data to their cluster-head where the aggregation ratio is set to 10%, then the length of the aggregated data is $(100 + (100 \times 0.1 \times 20))$ which is equal to 300 bits.

The LEACH cluster-heads forwards the aggregated data to the base station directly in all of the scenarios. However, CHEF, EEUC and EAUCF employ the EEUC multi-hop routing protocol [6] in Scenarios 2, 3, and 4. In Scenario 1, all of the algorithms forward the aggregated data to the base station via direct transmission.

In all of the scenarios, the desired percentage of cluster-heads for LEACH is set to 0.1. The α value of the CHEF algorithm is set

Table 4
Scenario 1: FND, HNA and total remaining energy.

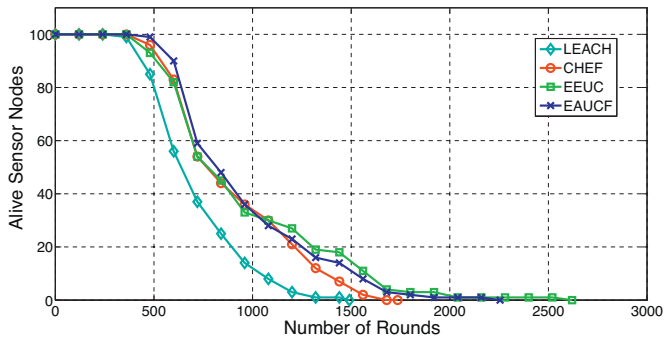| Algorithm	FND	HNA	Tot. rem. energy (J)
LEACH	358	626	24.32
CHEF	440	780	37.51
EEUC	424	769	37.76
EAUCF	487	818	40.36

Fig. 5. Scenario 1: distribution of alive sensor nodes according to the number of rounds for each algorithm.

EAUCF considers the energy level of each tentative cluster-head in its competition radius calculation. This means that if a tentative cluster-head has more energy, then it will have a greater cluster radius. In other words, it can serve more sensor nodes in the local region. This property ensures that EAUCF assigns more work to the cluster-heads which have more energy. This consideration makes EAUCF perform better than other algorithms for this scenario.

Fig. 5 depicts the distribution of the number of alive sensor nodes with respect to the number of rounds for each algorithm. This figure clearly depicts that deaths of sensor nodes for EAUCF begin after all the other algorithms.

The last column of Table 4 represents the total remaining energy for each algorithm at round 500. By using the information in this column, the energy efficiencies of the simulated algorithms are compared. Since every node has 1 J initial energy, the total energy of WSN is 100 J at the beginning. The battery of each sensor node depletes as the number of round increases. At round 500, LEACH has the lowest energy level which is approximately 24 J. The energy levels of EEUC and CHEF are nearly identical and approximately equal to 38 J. On the other hand, EAUCF has the highest energy level which is approximately 40 J. This result is parallel to the results which are inferred from FND and HNA metrics.

5.2. Scenario 2

In this scenario, the base station is located at the center of the wireless sensor network just like in Scenario 1. However, the CHEF, EEUC and EAUCF cluster-heads use the EEUC multi-hop routing protocol to forward their data packets rather than directly transmitting them to the base station. By comparing the results of Scenarios 1 and 2, the impact of using a multi-hop routing protocol instead of direct routing can be identified. The detailed configuration of this scenario is illustrated in Table 5.

The maximum competition radius is set to 40 and 70 m for EEUC and EAUCF respectively. These are the optimal maximum competition radius values for this scenario. After WSN is deployed, the maximum distance to base station is calculated as approximately 129.42 m. Table 6 indicates the results of Scenario 2.

Table 5
Configuration of Scenario 2.

Parameter	Value
Network size	200×200 m
Base station location	$(100, 100)$ m
Number of sensor nodes	100
Initial energy	1 J
Data packet size	4000 bits
ϵ_{amp}	100 pJ/bit/m^2
E_{elec}	50 nJ/bit
Aggregation ratio	10%

Table 6
Scenario 2: FND, HNA and total remaining energy.

Algorithm	FND	HNA	Tot. rem. energy (J)
LEACH	392	695	28.47
CHEF	599	765	38.30
EEUC	728	777	39.96
EAUCF	758	830	41.19

As shown in Table 6, EAUCF outperforms LEACH, CHEF and EEUC considering FND and HNA metrics. LEACH has the lowest performance, as in Scenario 1. In the first scenario, the FND values of CHEF and EEUC are close to each other. However, in this scenario EEUC is 23.2% better than CHEF considering the FND metric. Their HNA performances are still close to each other. EAUCF is 93.4% more efficient than LEACH, 26.5% more efficient than CHEF and 4.1% more efficient than EEUC according to the FND metric. If the HNA metric is considered for evaluation, the performance of EAUCF is 19.4% better than LEACH, 8.5% better than CHEF and 6.8% better than EEUC.

In this scenario, the LEACH again shows the lowest performance, because the reasons for low performance in the first scenario also apply to this scenario. The results of this scenario clearly indicate that unequal clustering algorithms, which are EEUC and EAUCF, perform better than LEACH and CHEF when the multi-hop routing protocol is used. This is because the batteries of the sensor nodes that are closer to the base station deplete faster. However, EEUC and EAUCF handle this situation by assigning smaller cluster sizes to the sensor nodes which are closer to the base station. On the other hand, CHEF cannot perform as well as EEUC and EAUCF, because it does not consider the hot spots problem. However, when CHEF's cluster-heads use the EEUC routing protocol instead of forwarding directly to the base station, it performs slightly better. Since EAUCF considers the energy level of the tentative cluster-heads during cluster radius calculation, the performance of EAUCF is considerably better than EEUC's.

Fig. 6 illustrates the distribution of the alive sensor nodes with respect to the number of rounds for each algorithm. This figure clearly shows that the proposed algorithm is more stable than the other algorithms, because sensor node deaths begin later for EAUCF and continue linearly until all sensor nodes die.

Fig. 7 shows the distribution of the number of clusters with respect to the number of rounds for each algorithm. The LEACH, CHEF and EEUC generate constant number of clusters until the first node dies, while the number of clusters generated by EAUCF increases. This is because the cluster radius is directly proportional to the energy level of each tentative cluster-head. If the energy level decreases, the cluster radius gets smaller. Therefore, the number of clusters is increased to cover all of the WSN.

The last column of Table 6 shows the total remaining energy levels for each algorithm at round 500. EAUCF seems to be the
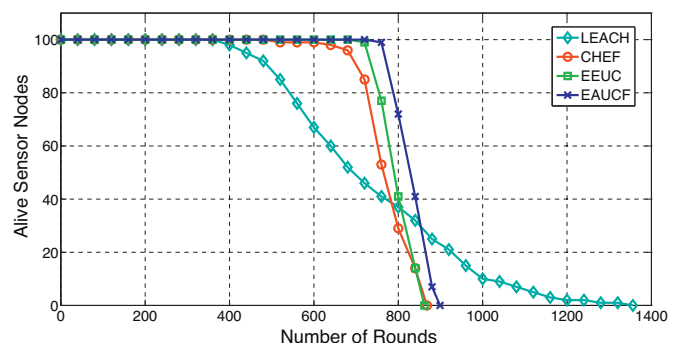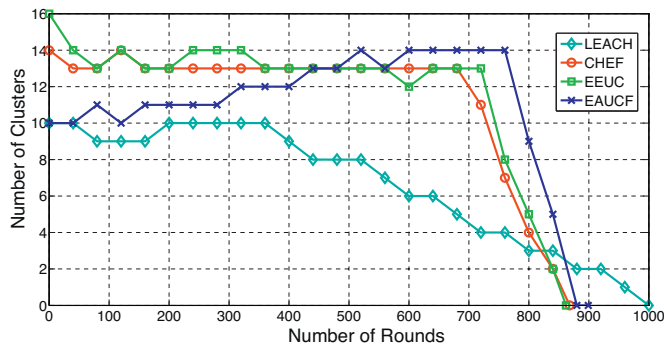

Fig. 6. Scenario 2: distribution of alive sensor nodes according to the number of rounds for each algorithm.

Fig. 7. Scenario 2: distribution of the number of clusters according to the number of rounds for each algorithm.

Table 7
Configuration of Scenario 3.

Parameter	Value
Network size	200×200 m
Base station location	$(100, 100)$ m
Number of sensor nodes	200
Initial energy	1 J
Data packet size	4000 bits
ϵ_{amp}	100 pJ/bit/m^2
E_{elec}	50 nJ/bit
Aggregation ratio	10%

most energy-efficient algorithm in this scenario, because it has the highest remaining energy level which is approximately 41 J. The remaining energy levels of EEUC and CHEF are close to EAUCF. On the other hand, LEACH has the lowest remaining energy level which is approximately 28 J. These results are parallel to the results inferred from the FND and HNA metrics.
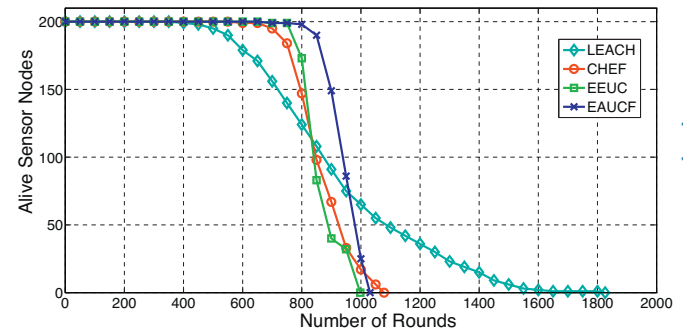
5.3. Scenario 3

In this scenario, the base station is located at the center of the wireless sensor network, as in Scenarios 1 and 2. The CHEF, EEUC and EAUCF cluster-heads use the EEUC multi-hop routing protocol for data transmission. In this scenario, the density of the deployed sensor nodes is twice that of Scenario 2. The aim of this scenario is to test the behaviors of the clustering algorithms in different sensor network topologies which have different numbers of deployed sensor nodes. The detailed configuration of this scenario is illustrated in Table 7.

The maximum competition radius is set to 35 and 70 m for EEUC and EAUCF, respectively. These are the optimal maximum competition radius values for this scenario. After the wireless sensor network is deployed, the maximum distance to the base station is calculated as approximately 137.93 m. The simulation of this scenario provides the results in Table 8.

As seen in Table 8, the simulation results of this scenario conform more or less with the simulation results of Scenario 2. However, the HNA performance of LEACH is increased significantly in this scenario with respect to Scenario 2. EEUC and EAUCF have the highest FND performance among the four clustering algorithms. LEACH

Table 8
Scenario 3: FND, HNA and total remaining energy.

Algorithm	FND	HNA	Tot. rem. energy (J)
LEACH	409	876	82.73
CHEF	618	849	92.32
EEUC	753	839	90.41
EAUCF	748	942	96.25

Fig. 8. Scenario 3: distribution of alive sensor nodes according to the number of rounds for each algorithm.

sensor nodes start to die earlier than the sensor nodes of the other algorithms. EAUCF is 82.9% more efficient than LEACH and 21.0% more efficient than CHEF considering the FND metric. The HNA performance of EAUCF is 7.5% higher than LEACH, that of CHEF 11.0% and that of EEUC 12.3%.

In this scenario, the FND performance of LEACH is significantly lower than the other algorithms. The FND performances of LEACH in Scenarios 1 and 2 are close to the performance in this scenario. The reasons for this low performance, which were provided in the former scenarios, are also valid for this scenario. Unequal clustering algorithms EEUC and EAUCF outperform LEACH and CHEF considering the FND metric, because they handle the hot spots problem when the multi-hop routing protocol is used for data transmission. If the HNA metric is considered, EAUCF performs slightly better than CHEF and EEUC in densely deployed sensor networks. In addition to this, LEACH's HNA performance is remarkable in this scenario, but still lower than the performance of EAUCF.

Fig. 8 shows the distribution of the alive sensor nodes according to the number of rounds for each simulated algorithm. As seen in this figure, the number of sensor nodes of the EAUCF algorithm is significantly greater than the other algorithms when the number of alive sensor nodes is 100. This situation implies that EAUCF keeps the wireless sensor network stable for longer time than the other algorithms.

The last column of Table 8 shows the total remaining energy levels for each algorithm at round 500. EAUCF has the highest energy level among all of the simulated algorithms, at approximately 96 J. In Scenarios 1 and 2, the remaining energy level of CHEF is nearly the same as that of EEUC. However, in this scenario CHEF has a higher remaining energy level, which is approximately 92 J. The sensor nodes of LEACH consumed much more energy up to round 500 than the other algorithms for this scenario.

5.4. Scenario 4

In this scenario, the base station is located at $(100, 250)$ m which is outside of the WSN. This is different from Scenarios 1, 2, and 3 in which the base stations are located at the center. If the results of Scenarios 2 and 4 are compared, it can be seen how the location of the base station affects the results of the simulations. The detailed configuration of this scenario is illustrated in Table 9.

In this scenario, the optimal maximum competition radius values are estimated as 60 and 110 m for EEUC and EAUCF, respectively. After WSN is deployed, the maximum distance to base station is calculated as approximately 260.28 m. The simulation of this scenario yields the results in Table 10.

As seen in Table 10, the values of the FND and HNA metrics for each algorithm have decreased with respect to the earlier scenarios. This is because the base station is located outside of the wireless sensor network. Thus, the cluster-heads consume much

Table 9
Configuration of Scenario 4.

Parameter	Value
Network size	200×200 m
Base station location	$(100, 250)$ m
Number of sensor nodes	200
Initial energy	1 J
Data packet size	4000 bits
ϵ_{amp}	100 pJ/bit/m^2
E_{elec}	50 nJ/bit
Aggregation ratio	10%

Table 10
Scenario 4: FND, HNA and total remaining energy.

| Algorithm	FND	HNA	Tot. rem. energy (J)
LEACH	173	339	27.18
CHEF	156	420	43.67
EEUC	342	423	44.68
EAUCF	397	445	46.47

more energy in transmitting their data packets to the base station. In this scenario, EAUCF has outperformed LEACH, CHEF and EEUC considering both FND and HNA metrics. CHEF has the lowest FND performance while LEACH has the lowest HNA performance. If the FND metric is considered, EAUCF is more efficient than LEACH by 129.5%, CHEF by 154.5% and EEUC by 16.1%. On the other hand, if the HNA metric is considered, the performance of EAUCF is greater than LEACH by 31.3%, CHEF by 6.0% and EEUC by 5.2%.

In this scenario, unequal clustering algorithms outperform LEACH and CHEF considering the FND metric. This implies that if smaller cluster-head radius values are assigned to the cluster-heads closer to the base station, the sensor node deaths can be delayed. This is the key observation in all of the scenarios. As it is also observed in the former scenarios, the radius calculation approach of EAUCF makes it perform better than EEUC. The results of this simulation show that unequal clustering approaches perform better even if the base station is located outside of the wireless sensor network. CHEF shows a remarkable HNA performance in this scenario, but its FND performance is the lowest. CHEF is a clustering algorithm which assigns a static cluster-head radius to all its cluster-heads. Therefore, it cannot handle the hot spots problem. Consequently, the sensor nodes start to die earlier than with EEUC and EAUCF which are unequal clustering algorithms.

Fig. 9 shows the distribution of the alive sensor nodes with respect to the number of rounds for each simulated algorithm. As seen in this figure, the sensor nodes of LEACH and CHEF start to die in the earlier rounds. The sensor node deaths for EAUCF start later than with all the other algorithms. EAUCF provides at least 400 stable rounds for this particular WSN.
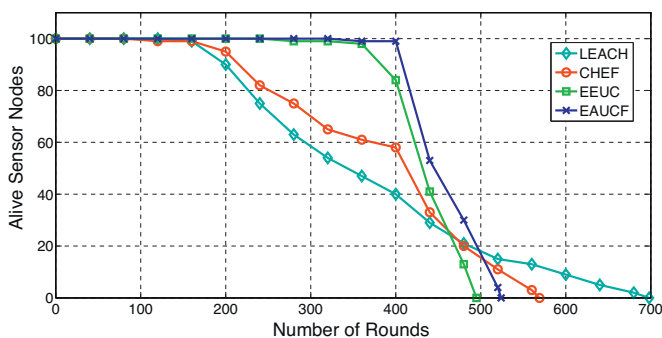
Fig. 9. Scenario 4: distribution of alive sensor nodes according to the number of rounds for each algorithm.
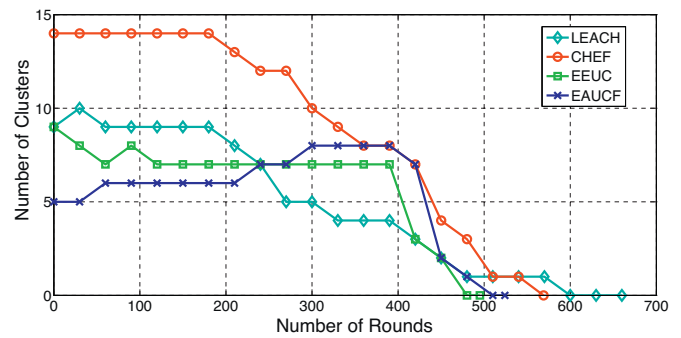
Fig. 10. Scenario 4: distribution of the number of clusters according to the number of rounds for each algorithm.

The distribution of the number of clusters with respect to the number of rounds for each algorithm is depicted on a fast line chart in Fig. 10. CHEF generates the highest number of clusters at the earlier rounds. On the other hand, EAUCF generates the lowest number of cluster-heads in the beginning. As the number of rounds increases, EAUCF starts to generate more cluster-heads until first node dies. This approach helps EAUCF to delay the sensor node deaths up to round 400.

Total remaining energy levels at round 250 for each algorithm are given in the last column of Table 10. EAUCF has the highest energy level, which is approximately 46 J. This data represents EAUCF as the most energy-efficient algorithm for this scenario. The remaining energy levels of CHEF and EEUC are close to each other. As it is also observed in the first scenario, LEACH consumes considerably more energy than the other algorithms.

6. Conclusion

The network relay traffic increases while getting closer to the base station in multi-hop WSNs. Therefore, the sensor nodes close to the base station tend to die earlier. In this paper, an energy-aware fuzzy unequal clustering algorithm, namely EAUCF, is introduced to solve this hot spots problem. The radius adjustment mechanism of this algorithm solves the problem by reducing the intra-cluster work of the cluster-heads closer to the base station. EAUCF aims to distribute the workload among all sensor nodes evenly. In order to achieve this goal, it mostly focuses on assigning appropriate cluster-head competition ranges to the sensor nodes. EAUCF calculates the competition radius values of tentative cluster-heads by considering their remaining energy and distance to the base station.

According to the simulation results, EAUCF has a better performance compared to LEACH, CHEF and EEUC. In all of the scenarios except Scenario 3, the sensor nodes that are clustered with EAUCF start to die later than the sensor nodes that are clustered with other algorithms. In Scenario 3, EEUC and EAUCF sensor nodes start to die in nearly the same round.

EAUCF outperforms all of the algorithms when the HNA metric is used in evaluation. This result implies that the workload is distributed evenly among all sensor nodes and the sensor nodes tend to die later within the lifetime of the WSN. Moreover, in all of the scenarios the total remaining energy level of EAUCF at a certain round is higher than with the other algorithms. Therefore, EAUCF is more energy-efficient than the other tested clustering algorithms. As a result of these experiments, it is concluded that EAUCF is a stable and energy-efficient clustering algorithm for wireless sensor networks.

EAUCF is designed for WSNs that have stationary sensor nodes. In future work, the fuzzy unequal clustering approach of the algorithm can be extended for handling mobile sensor nodes. In

cluster-head competition, only the residual energy and the distance to the base station of the tentative cluster-heads are taken into account. Some additional parameters such as node degree, density and local distance may also be utilized to further improve the performance of EAUCF.

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