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Distributed Fuzzy Controller Based Unequal Clustering Approach for Wireless Sensor Networks

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Abstract. *In order to solve 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 wireless sensor networks (WSNs), a Distributed Fuzzy controller based Unequal Clustering approach (DFUC) is proposed in this paper. DFUC aims to decrease the intra-cluster work of the cluster heads that are either close to the base station or have low residual energy. And the fuzzy controller is adopted to handle uncertainties in communication radius competition and cluster head election with input variables residual energy, node centrality, node degree and distance to base station and output variables chance and radius based on the IF-THEN rules, so as to make the optimal nodes be elected as cluster heads with appropriate cluster size. Furthermore, reclustering on demand is used to reduce the energy dissipation of the consecutive clustering in rounds. The experiment results show that DFUC performs better than its counterparts in terms of energy efficiency, number of message transmissions, and network lifetime. Therefore, DFUC is a stable and energy efficient unequal clustering approach to be utilized in WSN applications.*
Keywords: Wireless sensor networks, Unequal clustering, Fuzzy logic, Energy efficiency

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1. **Introduction.** A wireless sensor network (WSN) consists of numerous low cost, low power, multifunctional nodes which collect data through the collective work. And WSNs have been widely investigated and deployed in a variety of environments to support healthcare, emergency response, environmental monitoring, and space exploration et al, [1, 2]. The impact from environments together with energy constraints of the nodes makes high energy efficiency as well as long lifetime still a major design goal in WSNs [3]. Clustering is one significant way to achieve this task by organizing the sensor nodes with near locations into disjoint groups called clusters [4, 5], where each cluster has a cluster head (CH) with the purpose of gathering data from the cluster members (CMs), aggregating the gathered data and sending it to the base station (BS). At the same time, the CMs gather data from the environment and transmit it to their CHs [6–9]. By this way, the amounts of transferred data and inference as well as overheads in communication are significantly

reduced. Consequently, the network scalability, energy efficiency, real-time performance and lifetime are improved greatly [2, 4, 9].

There has been a substantial amount of research on clustering approaches for WSNs [1, 15], which can be divided into two categories namely equal clustering and unequal clustering. Equal clustering mechanism is used to form the clusters with relatively equal size, which means that each cluster includes nearly equal number of nodes to ensure that CHs are distributed evenly over the network and each cluster has almost the same coverage area [9, 10]. However, there is a major problem for this type of clustering that the traffic load is not evenly distributed among all the nodes because the nodes in the vicinity of the BS have to relay more data than farther ones, consequently the energy of them is dropped in a faster rate, which is typically known as the hot spot [3, 4]. To solve this problem, unequal clustering is provided to balance the load [3, 11], which makes the closer cluster to the BS be smaller in size. It is obvious that the smaller the number of cluster members, the less the rate of intra-cluster energy consumption. Thus, such CHs could save more energy for relaying the data received from farther clusters. Moreover, most of the existing methods maintain the created clusters by reclustering in rounds, which increase the energy dissipation of the network due to the overhead of consecutive clustering. So the on demand reclustering methods have provided to deal with this problem [9], which triggers the reclustering process when a certain parameter such as residual energy becomes less than the predefined threshold so as to save the energy consumed by the continuous clustering phases.

This paper proposes an unequal clustering algorithm DFUC based on fuzzy logic principle. DFUC elects an optimal node as CH based on its residual energy, node centrality, distance to BS, and assigns the appropriate competition radius according to its residual energy, node centrality, and distance to base station for the CH. After clusters are formed, data is transmitted by TDMA mechanism like in [3]. Moreover, reclustering on demand instead of in rounds is performed in order to reduce the energy dissipation due to the overhead of consecutive cluster formation phases. Because of the restriction in communication radius and the cluster maintaining mechanism for a CH, even load, reduced energy and long lifetime are achieved while the hot spot problem is solved in DFUC.

The rest of this paper is organized as follows. The related works are briefly explained in Section 2. The system model for DFUC is presented in Section 3, and the detail description of DFUC is shown In Section 4. In order to evaluate the performance of DFUC, comparisons are conducted with its counterparts by using the simulation method in Section 5, and the paper is concluded in Section 6.

2. **Related Works.** In the literature, a number of clustering algorithms have been proposed for WSNs. Low-Energy Adaptive Clustering Hierarchy (LEACH) [6] is one of the earliest and well-known clustering algorithms, which uses a probabilistic approach for selecting the CHs and assures that all the nodes in the network get selected as CH for at least once in a certain round. Moreover, the CHs newly formed communicate with their CMs by a TDMA mechanism so as to make CMs forward their sensed data in allotted timeslots, then aggregate the collected data and send it to the BS directly. Simplicity, distribution, balanced load, low overhead and configurable number of CHs LEACH is, however, direct communication between CHs and BS makes the farther CHs deplete energy at a faster rate, and thus the network cannot be implemented in large scales. More importantly, electing CHs randomly and not considering their energy lead to distribute CHs unevenly and elect the nodes with low energy as CHs. In order to improve the performance of LEACH, several further studies are presented in [7–9]. By taking the node degree and node centrality into account, EADC-FL [9] overcomes the shortcoming

of unevenly distributed cluster head as enjoyed by the LEACH. And the residual energy is used as the primary parameter to elect the candidate cluster heads so as to make the sensor nodes with the higher energy have more chance to be elected as the candidate CHs. Subsequently, each node calculates the value of its cost using fuzzy logic with inputs of node degree and node centrality. Thus, the candidate CH whose cost is the least will be elected as the final CH and finally clusters in equal size are constructed to make the energy consumption of cluster members balanced. Moreover, a routing tree is created for inter-cluster communication as in [10] in order to balance the energy consumption among the CHs. However, communication in multi-hop fashion among CHs inevitably makes the CHs in the vicinity of the BS take more data relay tasks and lose more energy compared to the father ones, which causes hot spot problem [3, 4].

Consequently, many unequal clustering algorithms are proposed to obtain even energy consumption and solve the hot spot problem [3, 4, 11, 16], which have been proved to be better than equal clustering in most forms of deployments [2, 4, 5]. DSBCA [11] considers the residual energy, connection density and times of being elected as the parameters to elect CHs so as to make the cluster much farther from the base station has larger cluster radius, or otherwise. Thus the balanced clustering structure is built and the network lifetime is enhanced. However, switching or reelecting cluster head only in the same or 'old' cluster could make the nodes at the edge of clusters be as CHs resulting in unbalanced energy consumption, even isolate the cluster from the network. So EAUCF [3] works in rounds as LEACH to maintain the unequal clusters. Besides, in EAUCF, the residual energy and distance to the BS are used for the computation of the tentative CHs' competition radius by a fuzzy logic system which can cope with different uncertainty in the network [12], and the tentative CH with highest residual energy within the cluster radius becomes the final CH. Afterwards, the CMs join the CH nearest to them. But in EAUCF, once much more number of nodes is close to the cluster near the BS, the energy of the CH depletes very quickly since many nodes close to the CH join in the cluster. To overcome this issue, FBUC [13] which is an improvement of EAUCF introduces one more variable node degree in the competitive radius computation where the competition radius determines the size of the cluster. Moreover, the CMs join in the CH based on the distance to the CH and cluster head degree which is the ratio of the number of nodes within its competition range of the total number of nodes using another fuzzy logic system so as to utilize the energy efficiently and to extend the network lifetime. The major drawback in EAUCF and FBUC is the restriction in number of members for a CH by the competitive radius, which leads to uneven energy consumption in the network. Also, these algorithms do not consider the energy consumption due to high intra cluster communication which affects the overall performance [4]. Therefore, to solve these problems, DUCF [4] assigns maximum limit of number of members for a CH based on its residual energy, node degree and distance to BS by a fuzzy output variable 'size' in order to balance the energy consumption. Moreover, DUCF uses the second fuzzy output variable 'chance' with the same inputs as 'size' for electing the CHs so as to make the node have higher 'chance' value than its neighbors elect itself as CH. Also, the CHs will check its 'size' for acceptance of new members when receiving a joining message. If the number of member nodes is more than its 'size' value, the CH send a message which indicates no space for the new member node. And this new member node will send another joining message for the next nearest CH apart from the previous one and this process continues till it joins a CH node. In the worst case, when a non-CH node cannot join any CH, it gets elected itself as CH. Afterwards, a TDMA mechanism is adopted to communicate among CH and its member nodes. Furthermore, a multi-hop data transmission scheme is used to reduce energy consumption in CHs. Though these related works show improvement than one another, less attention on fault tolerance of the nodes is paid to improve the reliability and extend the lifetime of the network.

However, the proposed algorithms perform reclustering in rounds which mitigates the energy consumption due to the cluster reconfiguration in each round [9]. Both ECPF [14] and EADC-FL [9] perform reclustering on demand during the steady phase. When a CH finds that its residual energy falls below the preset threshold, it sets a prespecified bit in a data packet which is ready to be sent to the BS in the current TDMA frame. Once the BS receives this data packet, it will inform the network to perform the cluster setup phase at the beginning of coming round. However, the threshold is difficult to be decided for real WSNs.

3. **System model.** DFUC can achieve load balance by forming unequal sized clusters with appropriate communication radius, and transmitting data by TDMA mechanism as in [3], as well as reclustering on demand. So the overall network lifetime is increased. In this section, the system model is described in detail including the network, energy and fuzzy controller models.

3.1. **Network model.** In order to simplify the network, the assumptions on the network properties are made as follows:

- N nodes $S = \{s_1, s_2, \dots, s_n\}$ are distributed in a square field, and each node s_i has a unique identity.
- Nodes are stationary after deployment with limited energy.
- Nodes are homogenous in terms of initial energy, processing power, memory, transmission and reception capabilities.
- The distance between nodes can be estimated by using received signal strength indicator (RSSI).
- During the very first time of deployment, distance to BS, distance to neighbors and number of neighbors will be computed at each node by Hello message interactions.

3.2. **Energy model.** The energy dissipated by transmitting l-bit message to the distance d is given by:

$$E_{tx} = \begin{cases} l * E_{elec} + \varepsilon_{fs} * d^2, & \text{if } d < d_0 \\ l * E_{elec} + \varepsilon_{mp} * d^4, & \text{if } d \geq d_0 \end{cases} \tag{1}$$

where E_{elec} is transmitter energy to run the transmitter or receiver circuitry and ε_{fs} ε_{mp} are energy dissipation values to run the amplifier for close and far distances with the threshold $d_0 = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$ respectively. Energy consumed in receiving l-bit message is calculated as follows:

$$E_{rx} = l * E_{elec} \tag{2}$$

Moreover, energy consumption due to data aggregation with l-bit is represented in Eq. (3).

$$E_{DA} = l * E_{pDb} \tag{3}$$

where E_{pDb} is energy consumption for single bit data aggregation.

3.3. **Fuzzy controller model.** Fuzzy logic is an efficient method used to solve various kind of problems in WSNs with lots of uncertainties, which is based on human decision-making behavior and human experience [4, 12]. Generally, fuzzy clustering algorithms merge different clustering parameters for CH election [1, 3, 4, 12]. As shown in figure1, DFUC uses a Mamdani fuzzy controller [4,9,12] which consists four basic elements: fuzzifier, inference engine, rule base and defuzzifier. Fuzzifier converts the crisp input data into appropriate fuzzy linguistic variable, rule base contains a set of fuzzy rules describing the dynamic behavior of the controller, and inference engine is used to form inferences and make decisions based on the fuzzy rules, defuzzifier converts the fuzzy output of inference engine into crisp values.

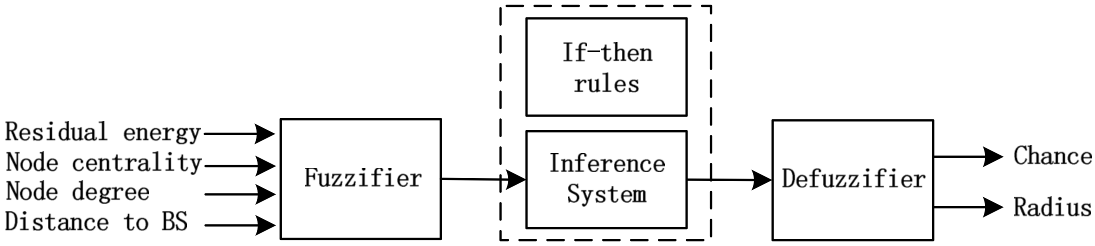


FIGURE 1. Fuzzy controller model of DFUC

The input parameters of the fuzzy controller are 'residual energy', 'node centrality', 'node degree' and 'distance to BS'.

- **Residual energy**: the remaining energy of a node, which is needed to perform the activities such as data collection, aggregation and aggregated data transmission.
- **Node centrality**: the value shows how central the node is among its neighbors proportional to the network dimension, which can be calculated from the Eq. (4).

$$Node\_centrality = \frac{\sqrt{\sum_{j \in N_i} d^2(i,j)} / |N_i|}{S_{area}} \tag{4}$$

Where $|N_i|$ is the number of neighbors of node i, and S_{area} is the size of the sensing field area.

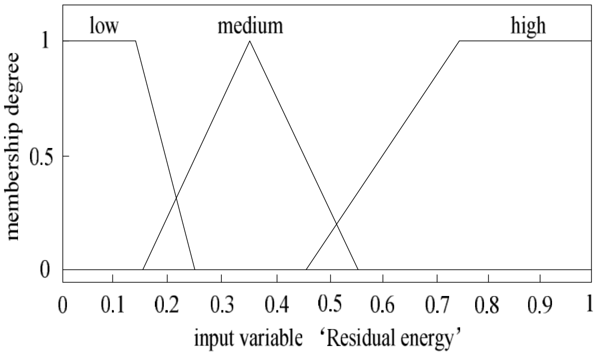
- **Node degree**: the number of neighbors within the communication radius of a node, which could reduce the intra cluster distance for a cluster.
- **Distance to BS**: the distance between node i and the BS, which is used to make the clusters in different sizes so as to avoid the hot spot problem.

Furthermore, DFUC has two output variables which are also called 'Chance' and 'Radius'.

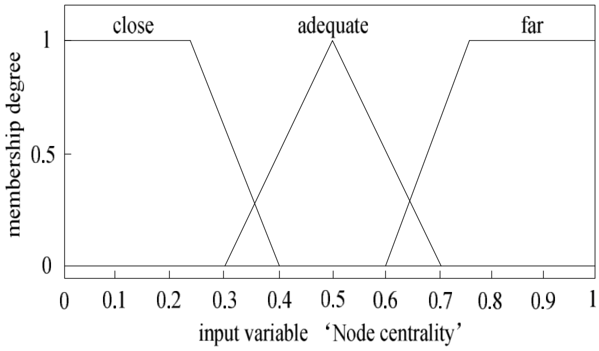
- **Chance**: the value shows the ability for a node to be selected as CH, which is based on residual energy, node centrality and distance to BS.
- **Radius**: the appropriate competition radius can be assigned for a particular CH, which is based on residual energy, node degree and distance to BS.

Next, the membership function for the inputs and outputs are given according to the experimental findings [3,4,12] and also from our own experimental results. *Low, medium, high* is the fuzzy linguistic variable for 'Residual energy', *close, adequate, far* for 'Node centrality', *little, medium, big* for 'Node degree', *distant, reachable, nearby* for 'Distance to BS'. *Low, high, close, far, little, big, distant and nearby* follows trapezoidal membership function, whereas the others have a triangular membership function. In addition, the output 'Chance' has nine linguistic variables and they are *very low, low, rather low, low medium, medium, high medium, rather high, high, very high.* The output 'Radius' has *very small, small, rather small, medium, rather large, large, very large* as its seven linguistic variables. The membership function for the inputs and outputs is depicted in figure2.

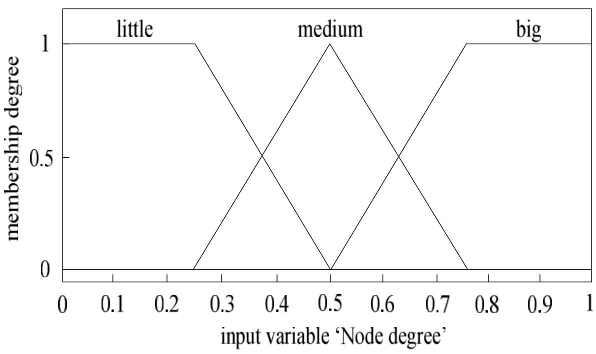
Based on the membership functions, the crisp input values are fuzzified to appropriate linguistic variable by the inference engine of the fuzzy controller. Then, the fuzzified variables are processed through the if-then rule base which consists of 54 rules, these rules are based on the mentioned above combination of different linguistic variables. The if-then rules are specified in table1.



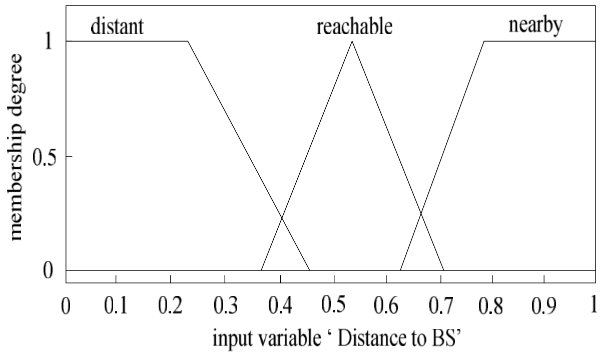
(a) Membership function for residual energy



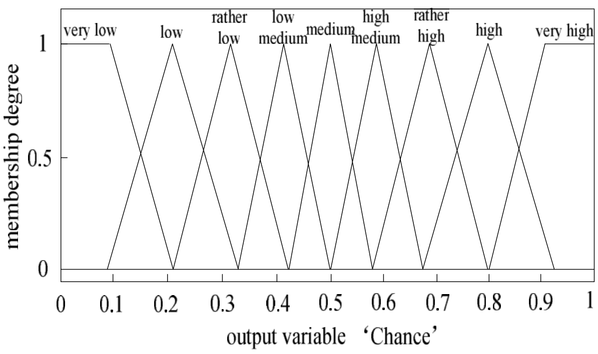
(b) Membership function for node centrality



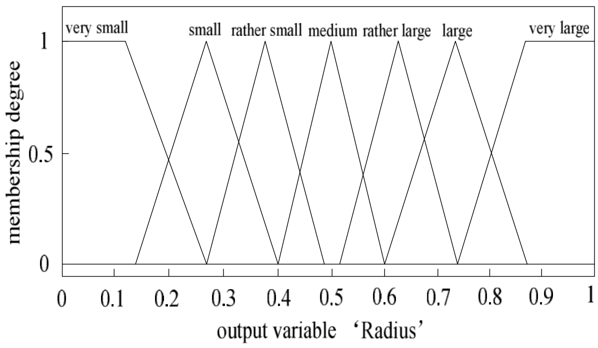
(c) Membership function for node degree



(d) Membership function for distance to BS



(e) Membership function for Chance



(f) Membership function for Radius

Figure 2. Membership functions for inputs and outputs

The output given by the inference engine is also a fuzzy linguistic variable, center of area method like in [4, 9] is used to defuzzify the outputs to crisp values 'Chance' and 'Radius'.

4. **DFUC Clustering Approach.**

DFUC adopts distributed fuzzy controller to calculate the 'Chance' and 'Radius' of each node so as to make the optimal nodes elected as CHs and appropriate competition radius assigned. DFUC works in two different phases: cluster formation and cluster maintenance.

4.1. **Cluster formation.**

Initially, each node calculates its 'Chance' and 'Radius' by the fuzzy controller. Then each node broadcasts a beacon message *Msg_Candidate* to its neighbors, and the *Msg_Candidate* message contains the node ID and 'Chance' value. The node with higher 'chance' value than its neighbors elects itself as CH and sends an *Msg_Head* message with its Radius. Of course, a node may receive more than one

Table 1. Fuzzy if-then rules

No.	input values				output values	
	energy	centrality	degree	distance	Chance	Radius
1	low	close	little	distant	very low	very small
2	low	close	little	reachable	very low	very small
3	low	close	little	nearby	low	small
4	low	adequate	medium	distant	very low	very small
5	low	adequate	medium	reachable	low	small
6	low	adequate	medium	nearby	rather low	rather small
7	low	far	big	distant	low	small
8	low	far	big	reachable	rather low	rather small
9	low	far	big	nearby	low medium	medium
10	middle	close	little	distant	low	rather small
11	middle	close	little	reachable	low	rather small
12	middle	close	little	nearby	rather low	medium
13	middle	adequate	medium	distant	low	medium
14	middle	adequate	medium	reachable	rather low	medium
15	middle	adequate	medium	nearby	low medium	rather large
16	middle	far	big	distant	rather low	medium
17	middle	far	big	reachable	low medium	rather large
18	middle	far	big	nearby	medium	rather large
19	high	close	little	distant	medium	medium
20	high	close	little	reachable	high medium	rather large
21	high	close	little	nearby	rather high	large
22	high	adequate	medium	distant	high medium	rather large
23	high	adequate	medium	reachable	rather high	large
24	high	adequate	medium	nearby	high	very large
25	high	far	big	distant	high	large
26	high	far	big	reachable	very high	large
27	high	far	big	nearby	very high	very large

Msg_Head message. In such case, it will choose to join the nearby CH by sending *Msg_Join* message. Once receiving the *Msg_Join* message, the CH updates its memList. When the cluster is finished, the CH broadcasts *Msg_list* message to its member nodes. The pseudo code of cluster formation is illustrated in figure3.

4.2. **Cluster maintenance.** After the clusters are created, each CH allocates a TDMA schedule for its CMs. Each CM is awake only during the assigned timeslot to transmit its sensed data [3]. The CH aggregates the received redundant data packets into a single packet and sends it to BS in multi-hop fashion [4]. Furthermore, reclustering on demand rather than in rounds is used to reduce the overhead of the approach and extend the network lifetime. Whenever the 'Chance' value of a CH is less than the average 'Chance' value of its CMs', the CH will set a prespecified bit in the data packet, which is prepared to be transmitted to the BS. Once the BS receives this data packet, it will inform the network to perform cluster formation. On-demand reclustering results in significant reduction of overhead by the continuous cluster formation phases. Consequently, the energy consumption of network decreases and the network lifetime extends. The pseudo code of on-demand reclustering is given in figure4.

Cluster formation

n = number of nodes, m = number of CHs, *hdList* = list of CHs, *memList* = list of CMs;
$n = N$, $m = 0$, S_i = the ith node in the network, *Si.state=iniState*;
for $i = 1$ to n do
    $memList_i = \varnothing$;
    $S_i.Er$ = ResidualEnergy, $S_i.Dn$ = NodeDegree, $S_i.Cn$ = NodeCentrality, $S_i.BSn$ = DistanceToBS;
    $Chance, Radius = FuzzyCtr(s_i.Er, s_i.Dn, S_i.Cn, s_i.BSn)$;
    sends and receives *Msg_Candidate* message to and from neighbors,
    $Msg\_Candidate = [MSG\_TYPE1, ID_i, Chance_i]$;
end for
for $i = 1$ to n do
    if $(s_i.Chance > s_j.Chance, \forall s_j \in N_i)$, N_i is the set of neighbors
        sends *Msg_Head* message $Msg\_Head = [MSG\_TYPE2, ID_j]$;
        $s_i.state = chState$, $m+ = 1$;
    else if (receives a *Msg_Head* message from node s_j)
        Adds an item to $hdList_j = \{\ldots, s_j\}$ ordered by the distance between s_j and s_i;
        sends *Msg_Join* message to the nearest CH_x
        $Msg\_Join = [MSG\_TYPE3, ID_i, CH\_ID_x]$;
        updates $hdList_j = \{\ \ldots, s_j\ \}$ by removing s_x;
    else if (receives a *Msg_Join* message from Sj)
        if $(s_i.state = chState)$
        sends a *Msg_Success* message to s_j, $Msg\_Success = [MSG\_TYPE4, ID_i, ID_j]$;
        adds an item to $memList_i$, $memList_i = \{\ \ldots, S_j\ \}$;
        end if;
    else if (receives *Msg_Success* message from s_j)
        $s_i.state = cmState$; $s_i.CH = s_j$; $hdList_i = \varnothing$;
    end if;
end for;

FIGURE 3. Pseudo code of cluster formation

Reclustering on-demand

m = number of CHs, *memList* = list of Members;
for $i = 1$ to m do
    calculates average 'Chance' $AverChance = \frac{\sum_{j=1}^{|memList_i|} s_j.Chance}{|memList_i|}$
    if $(s_i.Chance < AverChance_i)$
        sets a predefined bit in the data packet to inform BS;
    end if;
end for;
if (BS receives a data packet with predefined bit = True)
    broadcasts *Msg_Reclustering* message in the network;
end if;

FIGURE 4. Pseudo code of on-demand reclustering

5. **Simulation results.** In this section, simulations are conducted to evaluate the performance of the proposed algorithm DFUC, compared with DUCF [4], EAUCF [3] and

LEACH [6]. In the simulations, 100 nodes are deployed randomly in a square field of area $200\,\mathrm{m} \times 200\,\mathrm{m}$. The initial energy of each node is 1J. Every simulation result is the average of 50 independent experiments, and the parameters of the simulations are listed in table2. DFUC, DUCF, EAUCF and LEACH have been tested in different scenarios. In *Scenario 1*: BS node's location is $(100, 100)$, which is in the middle of region of interest; *Scenario 2*: BS node's location is $(200, 200)$, which is at the corner of region of interest. The scenarios are shown respectively in figure5. The circular points in figure5 represent sensor nodes and five-pointed star represents BS.

Table 2. Simulation parameters

Parameters	Values
l	4000
node initial energy	1J
E_{elec}	$50\,\mathrm{nJ} \cdot \mathrm{bit}^{-1}$
ε_{fs}	$10\,\mathrm{pJ} \cdot \mathrm{bit}^{-1}$
ε_{mp}	$0.0013\,\mathrm{pJ} \cdot \mathrm{bit}^{-1}$
E_{pDb}	$5\,\mathrm{nJ} \cdot \mathrm{bit}^{-1}$
d_0	87 m
data packet size	500 bytes
control packet size	25 bytes

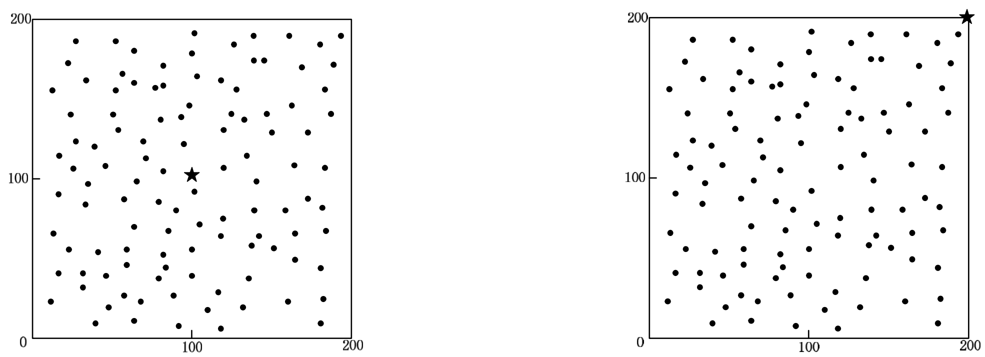
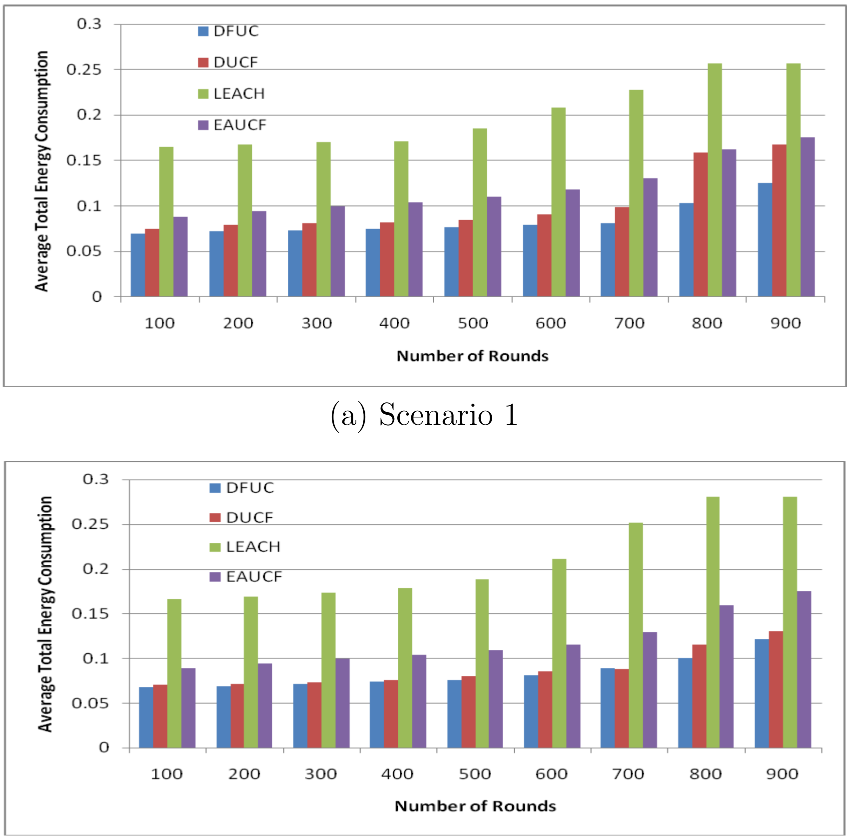


Figure 5. Network topology in two scenarios

Firstly, the average energy consumption per round is measured by using the four algorithms and the results are depicted in figure6. The results show that LEACH consumes more energy than the other algorithms because its CHs are elected randomly and communicate with BS directly. Since EAUCF considers the energy level of each tentative cluster-head in its competition radius calculation, it performs better than LEACH. However, it still lags behind DFUC and DUCF, because they don't have such a complicated calculation process in electing the cluster head. DFUC and DUCF assigns a proper number of member nodes to a CH based on its capacity so as to form unequal clusters. Moreover, DFUC reclusters on demand, which consumes less overhead than in rounds of DUCF. Thus, the proposed algorithm DFUC achieves the best energy efficiency.

Secondly, the number of useful messages over the time is performed to evaluate the communication efficiency. The results are given in figure7. EAUCF shows worst performance than others because it does not restrict the number of members in a cluster which will reduce the number of data message from individual nodes to BS. The same problem



(a) Scenario 1

(b) Scenario 2

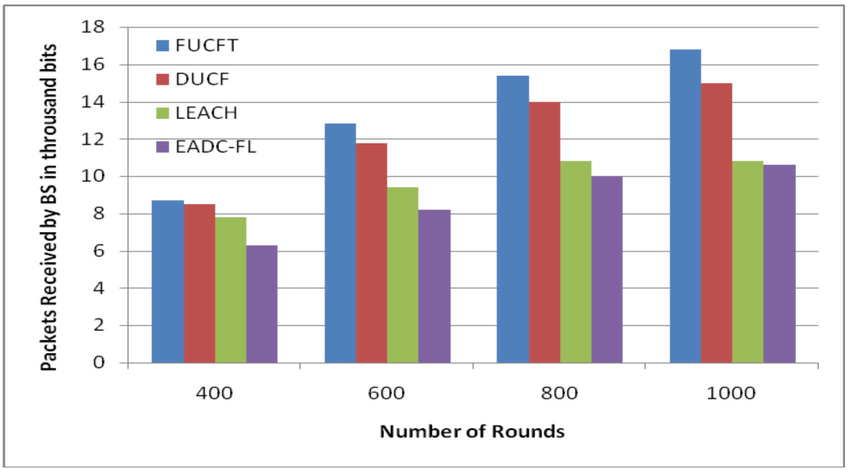
Figure 6. Average total energy spent per round

continues in LEACH which doesn't take care about the numbers of nodes in a cluster. DUCF gives better results than EAUCF and LEACH since it restricts the number of members through the second fuzzy output variable 'size'. Furthermore, DFUC reclusters on demand so as to significantly improve the communication efficiency of the network.

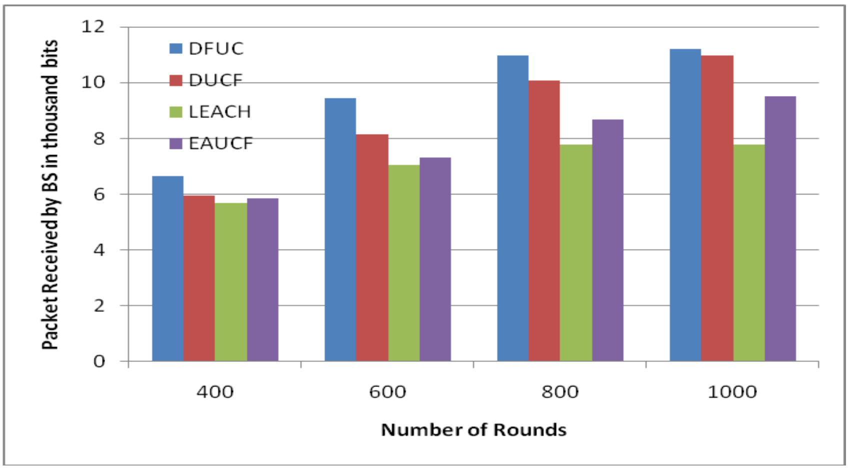
Finally, the performance comparison in terms of survival nodes which is used to evaluate the network lifetime is presented in figure8. Figure8 shows the average number of survival nodes in *Scenario 1 and Scenario 2.* It's obvious that DFUC outperforms DUCF, EAUCF and LEACH. The results show that LEACH has worst performance due to its without considering residual energy in CH selection so as to the sensor nodes with low energy may die prematurely and reduce the network lifetime. EAUCF selects the node with the most residual energy as CH, to a certain extent, the quality of cluster head is optimized. However, CH dies fast when there are many CM in a cluster. DUCF solves the problem of imbalanced energy consumption with unequal clustering to improve the network lifetime. However, reclustering in rounds in DUCF increases the energy dissipation of the network due to the overhead of consecutive clustering formation phases. Therefore, as time goes on, DFUC obtains more survival nodes than LEACH, EAUCF and DUCF due to its on demand reclustering scheme. Accordingly, the network lifetime is extended.

6. **Conclusion.**

A new unequal clustering algorithm based on distributed fuzzy controller DFUC is proposed for WSNs to decrease the traffic as well as extend the network lifetime. DFUC considers the residual energy, node centrality and distance to BS as parameters inputted into the fuzzy controller to evaluate the 'Chance' of the candidate CHs, a node with the maximum 'Chance' will be elected as CH. Moreover, DFUC forms the clusters



(a) Scenario 1



(b) Scenario 2

FIGURE 7. Number of packets received by the base station

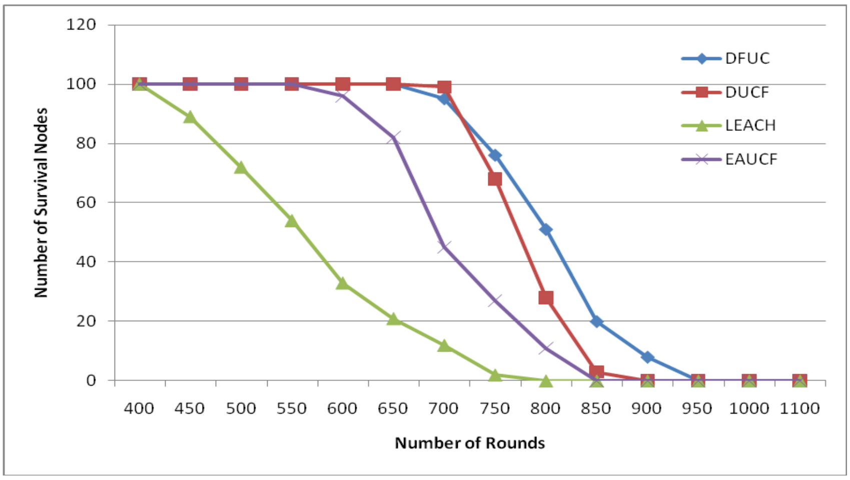


FIGURE 8. Comparison of survival nodes

with appropriate competition radius by considering residual energy, distance to BS and node degree so as to balance the energy consumption among the nodes. Reclustering on demand is used to reduce the energy dissipation of the consecutive clustering in rounds.

The simulation results show that DFUC outperforms other clustering algorithms, it can improve the energy consumption and lifetime of the network by forming optimal clusters, which makes it be suitable for many real time applications.

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