An Energy-Balanced Unequal Clustering Approach for Circular Wireless Sensor Networks

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Abstract—**The network lifetime of the Wireless Sensor Networks (WSNs) is a critical factor for the relevant applications due to the limited energy supply. However, the imbalanced energy consumption of the whole network always leads to the "Hot Spot Problem" and the decline of network lifetime inevitably. To this end, the schemes of energy-balanced unequal clustering and energy-efficient cluster head rotation are considered in this paper. To be specific, we conduct detailed theoretical derivation and mathematical calculation based on the concept of gradient to obtain the optimal number of CHs, with the aim of balancing the energy consumption for the whole network topology. In addition, a fuzzy logic-based mechanism for CHs rotation is also proposed to balance the energy distribution among different cluster heads. Subsequently, a novel Energy-Balanced unequal Clustering Approach (EBCA) for circular wireless sensor networks is proposed and detailed. Finally, we conduct extensive simulations to verify its performance. The experimental results indicate that EBCA is able to balance the energy consumption of cluster heads in different gradient, reduce the energy consumption and prolong the network lifetime effectively compared with the classic and latest clustering algorithms.**

Index Terms—**WSNs, Energy Balance, Network Lifetime, Clustering Algorithm.**

I. INTRODUCTION

WIRELESS SENSOR NETWORKS (WSNs) is a kind of network which have been applied in extensive applications. In the past few years, WSNs play an important role in environmental monitoring, target tracking, security maintenance, military defiance, and medical care, *etc.* [1-3]. Meanwhile, WSNs contribute to the current hot topics in academics and industry, such as the Internet of Things, Big Data, and so on [4-6].

In general, WSNs consist of thousands of tiny and inexpensive electronic devices, *i.e.*, sensor nodes. They are capable of obtaining the required data, such as temperature, humidity, or light from surroundings and communicating with other nodes through wireless communication links. The target of the network is to transmit the acquired data to the Sink. In reality, the sensor nodes are supplied with limited energy and usually deployed in harsh environments on a large scale. As a result, it's impractical or impossible to replenish them due to the high cost [7].

Recently, various techniques have been developed to reduce the energy dissipation and prolong the network lifetime, such as mobile relays and sinks, data gathering, policy-based relaying with cross-layer design, and optimization algorithms, and so on [8-10]. One of the most remarkable techniques is the clustering algorithm which improves the energy efficiency through multi-hop transmission [11]. In clustering algorithms, all the sensor nodes are grouped into a set of clusters which consist of one Cluster Head (CH) and several Cluster Members (CM). The function of CM is to acquire valid data and transmit them to the CH. The CH collects the data from its CMs and forwards them to the inner CHs closer to the Sink. Through the clustering algorithm, the sensor nodes with limited energy transmit valid data to the CH instead of propagating them to the Sink directly, which decreases the total transmission overhead and extends the network lifetime accordingly.

The clustering algorithms can be divided into two categories: equal-sized clustering algorithm and unequal-sized clustering algorithm. For the equal-sized clustering algorithm, the CHs near the Sink transmit a larger amount of data and deplete more energy than those further away from the Sink, which means the CHs closer to the Sink exhaust energy more quickly [12, 13]. Consequently, the energy distribution becomes uneven [14] and the network will be partitioned into pieces ahead of time, which is referred to as the "Hot Spot Problem". According to [15], the nodes far away from the Sink still have at least 90 percent of the initial energy when those close to the sink run out

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of all of their energy. But for the unequal-sized clustering algorithms [16-18], the sizes of clusters are determined by their position. In general, the clusters closer to the Sink are smaller in size, which helps to reduce the intra-cluster traffic burden on the CHs close to the Sink. Therefore, it makes the energy consumption distribution more balanced. As a result, the network lifetime is prolonged effectively [19].

To this end, we proposed an Energy-Balanced unequal Clustering Approach for the circular wireless sensor network (EBCA) in the paper. It aims to improve the energy efficiency and extend the network lifetime for the circular wireless sensor network. Specifically, the major contributions of our work can be summarized as follows,

1) we conduct extensive theoretical derivation and mathematical calculation based on the concept of gradient to obtain the optimal number of CHs, with the aim of balancing energy consumption for the whole network topology. In addition, a fuzzy logic-based mechanism for CHs rotation is proposed to balance the energy consumption distribution.

2) An Energy-Balanced unequal Clustering Approach (EBCA) for circular wireless sensor network based on the optimal number of CHs algorithm and fuzzy logic-based CH rotation mechanism is proposed in detail in this paper.

3) Extensive simulations have been conducted to verify the energy efficiency of EBCA by comparisons with the classic and the latest clustering algorithms, such as LEACH, OCCA, and EEUCA. The results show that EBCA outperforms the other three clustering algorithms definitely.

The remainder of this paper is organized as follows. Section II reviews the related works, followed by Section III which describes the network model and the relevant preliminaries. Section IV presents the theory foundation of EBCA. Section V details the specific energy-balanced algorithm of EBCA. In section VI, we evaluate the performance of EBCA through extensive simulations. Finally, we draw the conclusion and point out some potential future directions.

II. RELATED WORKS

In recent years, many clustering algorithms have been proposed and utilized to improve the energy efficiency of WSNs. There exist some important clustering algorithms, which are based on the random clustering mechanism, the fuzzy logic-based mechanism, and mathematical calculation mechanism respectively.

Random clustering is an effective mechanism for WSNs. The first dynamic clustering algorithm presented for WSNs is LEACH [20]. It's a distributed algorithm that selects CHs randomly to balance energy consumption of nodes in the whole network topology. CHs receive and aggregate data from CMs and transmit them to the Sink through multi-hop transmission in every round. However, due to the feature of random selection, it's possible for a node with lower energy to be elected as a CH, which makes it difficult to extend the network lifetime. Consequently, a new clustering approach, HEED, was proposed to alleviate the drawback of the LEACH [21]. HEED enlarges the probability of being selected as CHs for the nodes with higher residual energy, which contributes to balancing the energy consumption of CHs effectively.

The fuzzy logic-based mechanism is usually adopted to form clusters with unequal sizes. In DUCF [22], the residual energy, the node degree, and the distance to the Sink are adopted as three input variables, and the probability of CH and cluster size are obtained through the fuzzy logic inference. Similarly, an optimized scheme is proposed in [23]. The probability of being CH and the cluster size are acquired through fuzzy inference rules on the basis of five input variables, *i.e.*, the residual energy, the distance to the Sink, the distance to neighbors, the node degree, and the node centrality respectively. With the output variables, the clusters can be formulated in a controllable way. In [24], the authors regarded the residual energy, the number of neighbors, and the quality of communication links as the input variables to elect CHs. As for [25], the fuzzy logic was utilized to determine the competition radius, the criteria of CH election, CM's participation and cluster head rotation for the next round. In [26], UCT2TSK was proposed, which was based on the interval type-2 TSK fuzzy logic theory. In UCT2TSK, the relative distance to the Sink, the residual energy, and the node density were adopted as inputs of the interval type-2 fuzzy logic. All the related fuzzy logic-based algorithms are summarized as shown in Table I. The fuzzy logic-based mechanism is more flexible, however, the clustering protocols based on fuzzy logic cannot guarantee coverage sometimes.

TABLE I

SUMMARY OF REVIEWED FUZZY APPROACHES

Protocol	*Input parameters*	*Output parameters*
[22]	Residual energy Node degree Distance to Sink	CH selection Cluster size
[23]	Residual energy Distance to Sink Distance to neighbors Node degree	CH selection Cluster size

[24]	Node centrality Residual energy Number of neighbors Communication links	CH selection
[25]	Residual energy Distance to the Sink Node density Distance to CH	Competition radius Criteria of CH election CM's participation Rotation for next round.
[26]	Distance to the Sink Residual energy Node density	CH selection Cluster size

The mechanism based on mathematical calculation is another significant means to obtain the unequal clusters. In [27], a new mechanism was based on the arrangement of nodes and the information of nodes' distribution, which contributed to the reduction in energy overhead considerably. In [28], an improved *K*-means algorithm was proposed to generate clusters. Using the weighted evaluation function, the optimal cluster structure was obtained for the whole network. In order to develop traditional uneven clustering algorithms, a distributed clustering approach was presented to form traffic-balanced clusters in [29] and generate balanced clusters with the consideration of specific thresholds for cluster formation. A scheme for Arraying Cluster size and Transmission (ACT) range was proposed in [30]. The author utilized the theoretical analysis to calculate the cluster size and makes the energy dissipation of CHs more balanced. However, ACT cannot guarantee the coverage rate and the process of calculating is not accurate enough. In [31], the network area is divided into virtual grids and the size of grid-based clusters in each level are acquired by equalizing the energy dissipation of CHs and minimizing the total energy consumption of CHs. Xiang, *et al* calculated the optimal one-hop distance between two adjacent rings and the same clustering angle in every ring in [32], which were formulated by minimizing the difference in energy consumption between inter-cluster and intra-cluster communication. Under the conditions presented in [33], the clustering angle can be acquired by minimizing the energy consumption through calculation expression. In [34], an optional energy-aware clustering algorithm (OCCN) was proposed based on the optimal distance of one hop proposed in [32]. The circular network was divided into equal clusters and the optional number of clusters was obtained to reduce the total energy consumption. However, neither [32] nor [33] takes the load balance of CHs into consideration, which leads to the network partition early. In [34], the network was grouped into equal-size rectangular units. The size of clusters in each unit was elaborately designed based on the level of node's residual energy and the number of clusters. An Energy-efficient and Coverage-Guaranteed Unequal-sized Clustering algorithm for WSNs (ECUC) was proposed in [35]. ECUC aims to adjust the bound of sectors to improve energy efficiency. The upper bound was determined based on the node density and the lower bound was computed according to the energy consumption by Integer Linear Programming.

There are some shortcomings in existing works in terms of energy efficiency and the network performance of WSNs. For instance, some random clustering algorithms lead to the decline of energy efficiency and network lifetime. Besides, the "Hot Spot Problem" has not been put enough emphasis. At the same time, the mathematical calculation mechanism wasn't accurate enough since the suitable mechanism of CH selection and rotation to balance energy consumption wasn't utilized. To this end, this paper aims to address the deficiencies above. The energy burden on sensor nodes is analyzed and calculated through extensive theoretical derivation and mathematical calculation, with the aim of making energy consumption more balanced. Meanwhile, a fuzzy logic mechanism is proposed to control the process of CHs rotation. With these measures, the energy consumption difference between nodes further away from the Sink and nodes closer to the Sink can be minimized, which is able to alleviate the "Hot Spot Problem".

III. Preliminaries

A. Network model

Similar to [30-33, 35], the network in this paper consists of a large number of homogeneous sensor nodes. All of the sensor nodes keep stationary and are randomly distributed in a circular area. To cut down the energy overhead for transmission, they are organized into separated clusters. The Sink is deployed in the center of the network topology. All of the nodes possess the same initial energy. Besides, all of them are set to the same transmission range. The CMs collect their data for the corresponding CH and the latter transmits the data from outer clusters and itself towards the inner clusters. Each sensor node is aware of its location in the network and has a unique ID.

The network topology is divided into several rings with the width of r in this paper. The clusters in different rings have distinct center angles and each ring consists of different number of clusters with the same center angle (as shown in Fig. 1).

B. Energy consumption model

The energy consumption of sensor nodes mainly consists of three parts, namely the energy for sensing, transmitting, and receiving. In general, the energy consumption for sensing is always ignored because it's too tiny, as shown in [31]. The energy consumption for transmitting is denoted as E_t. E_t is defined as follows when sensor node i transmits one bit message to node j,

$$E_t = E_{elec} + E_{amp} \times d^{\alpha} \tag{1}$$

where E_{elec} is the electronic energy, which is related to other factors such as digital coding and modulation. E_{amp} is the transmitting amplifier and d is the transmission distance between nodes i and j. α is the path loss exponent and it is 2 for the free space transmission environment. As for the receiver, the energy overhead for reception (E_r) is consumed as below when receiving one-bit message,

$$E_r = E_{elec} \tag{2}$$

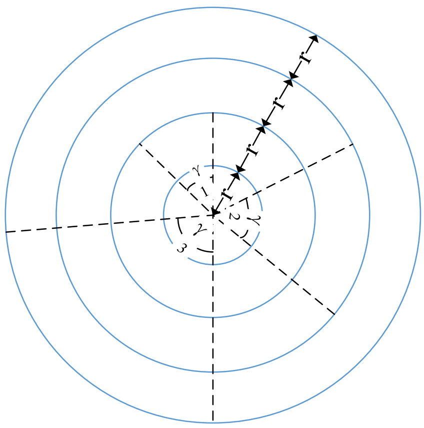

Fig. 1. Width of rings and center angles of different rings of the network topology in this paper.

C. Fuzzy logic

Fuzzy logic has been widely applied in adaptive control systems and system identification since it was proposed. It is featured by easy implementations, robustness, and the ability to approximate any nonlinear mapping [36]. In general, the fuzzy system always consists of four components, which is illustrated as shown in Fig. 2.

1. Fuzzification: each crisp input is converted to a language description.
2. Fuzzy Rule Set: through a set of if-then rules, the inputs after fuzzification are used to obtain the final outputs described by the language description.
3. Defuzzification: it transforms the fuzzy outputs into crisp outputs.
4. Membership Function: it is a specific relationship between the input and fuzzification as well as that between the output and defuzzification.

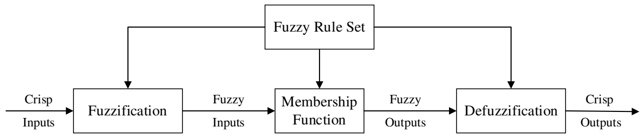

Fig. 2. Typical structure of fuzzy system.

IV. Relevant Theory Foundation concerning Fuzzy Logic-based Clustering in this Paper

According to the network topology, the number of clusters as well as that of CHs in the ith ring can be expressed as follows,

$$C_i = \frac{2\pi}{\gamma_i} \tag{3}$$

where γ_i is the center angle of the ith ring. The CHs in the ith ring receive the data from the upper cluster. The area of its upper rings S_i can be denoted as follows,

$$S_i = \pi(nr)^2 - \pi(ir)^2 \tag{4}$$

where n is the number of rings. In the ith rings, CHs receive the data from its own cluster and the upper clusters. The total amount of data P_i that are transmitted by every CH in the ith ring per second is obtained as below,

$$P_i = \frac{\rho\lambda S_i}{C_i} + \frac{\pi(ir)^2 - \pi((i-1)r)^2}{C_i}\rho\lambda = \frac{[n^2 - (i-1)^2]}{C_i}\rho\lambda\pi r^2 \tag{5}$$

where λ represents the number of bits in one packet within the fixed time interval and ρ is the node density of the whole network. For the sake of energy equilibrium, the energy analysis is conducted in this paper. The energy depleted by the CHs consists of three parts, including the energy for receiving data from other CHs E_{RCH}, for the data from its cluster members E_{RCM}, and the energy for transmitting all the data to the inner ring E_{TR}. Therefore, the energy consumption of CH in the ith ring can be expressed as follows:

$$E_{i-RCH} = \frac{C_{i+1} \times P_{i+1}}{Ci} E_{elec} \tag{6}$$

$$E_{i-RCM} = \frac{\pi(ir)^2 - \pi((i-1)r)^2}{C_i} \rho\lambda E_{elec} \tag{7}$$

$$E_{i-TR} = P_i(E_{elec} + E_{amp} \times r^2) \tag{8}$$

$$E_{i-CH} \cong E_{i-RCH} + E_{i-RCM} + E_{i-TR} = P_i(2E_{elec} + E_{amp} \times r^2) \tag{9}$$

On the basis of Expression (9), the total energy consumption of CHs in the ith ring can be obtained. In order to achieve energy equilibrium among CHs in different rings, it is necessary to satisfy the following condition,

$$E_{1-CH} \approx E_{2-CH} \approx \cdots \approx E_{n-CH} \tag{10}$$

Expression (10) is applied to calculate the proportion of clusters as well as the center angle among different rings. Nevertheless, the specific quantity of CHs in each ring is not able to be obtained. In this paper, we aim to balance the energy consumption of CHs and reduce the total energy consumption of the whole network. Combining two essentials mentioned above, we analyze the relationship between the total energy consumption and the number of CHs with the consideration of Expression (10), which ensures the energy consumption of CHs is equivalent approximatively. Subsequently, the total energy consumption can be repressed as follows,

$$E_{total} = \sum_{i=1}^{n} E_i, \quad 1 \le i \le n \tag{11}$$

As shown in Expression (11), the total energy consumption is the sum of energy consumption for each ring E_i. To minimize the energy consumption, E_i is necessary to be analyzed through the expression as follows,

$$E_i = C_i \times (E_{i-CH} + E_{i-nonCH}) \tag{12}$$

where C_i is the number of the clusters in the ith ring. E_{i-CH} denotes the energy consumption of each CH in the ith ring, which can be calculated according to Expression (9) and $E_{i-nonCH}$ represents the energy consumption of non-cluster head nodes in the ith ring. In the fixed time slot, the non-cluster head nodes transmit data to its CH. To be specific, the energy consumption of a non-cluster head node is expressed as below,

$$E_{i-nonCH} = \frac{\pi(ir)^2 - \pi((i-1)r)^2}{C_i} \rho\lambda \times \left(E_{elec} + E_{amp} \times d_{tCH}^2\right) \tag{13}$$

where d_{tCH} denotes the average distance from the CMs to their CHs. Assume that CH locates at the center of a cluster and each cluster is a circle. Meanwhile, transform the Cartesian coordinates into Polar coordinates. The average distance from the center to all the nodes in the cluster can be expressed approximately as below,

$$\mathrm{d}_{tCH}^2 = \iint \left(x^2 + y^2\right) \rho(x, y)\, dxdy = \iint R^2 \rho(R, \theta) R dR d\theta \tag{14}$$

The actual area of the cluster in the ith ring can be obtained as follows,

$$S_{cluster} = \frac{\pi(ir)^2 - \pi((i-1)r)^2}{C_i} \tag{15}$$

Because the cluster is regarded as a circle with the radius of R, the area of the cluster is denoted as follows,

$$S_{cluster} = \pi R^2 \tag{16}$$

By means of combing Expressions (15) and (16), it is easy to obtain $R = r\sqrt{\frac{i^2 - (i-1)^2}{C_i}}$. Consequently, d_{tCH} can be denoted as follows,

$$d_{tCH}^2 = \rho \int_0^{2\pi} \int_0^{r\sqrt{\frac{i^2-(i-1)^2}{C_i}}} R^3 dR d\theta \tag{17}$$

According to Expression (17), (13) can be redefined as

$$E_{i-nonCH} \cong \frac{\pi(ir)^2 - \pi((i-1)r)^2}{C_i} \rho\lambda \times \left(E_{elec} + E_{amp} \times \frac{\rho\pi r^4 (2i-1)^2}{2C_i^2}\right) \tag{18}$$

Combing Expressions (9), (12), and (18), E_i can be redefined as follows,

$$\begin{aligned} E_i &\cong \rho\lambda\pi r^2\left[n^2 - (i-1)^2\right] \times \left(2E_{elec} + E_{amp} \times r^2\right) \\ &+ \left[\pi(ir)^2 - \pi((i-1)r)^2\right] \rho\lambda \times \left(E_{elec} + E_{amp} \times \frac{\rho\pi r^4 (2i-1)^2}{2C_i^2}\right) \end{aligned} \tag{19}$$

On the basis of (19), Condition $\frac{d}{dC_i}(E_i) < 0$ can be established. Therefore, it can be concluded that E_i is a decreasing function of C_i. Specifically, E_i decreases with the increase of C_i. Namely, the more the number of clusters C_i is, the less energy all nodes consume under constraint (10). Therefore, it is necessary to make the sensor nodes in the first ring all become CHs to minimize the value of E_{total}. As a result, the number of clusters reaches the maximum on the premise of Constraint (10).

Theorem 1. When the sensor nodes in the first ring select out their CH, the number of clusters in the whole network will reach the maximum.

Proof. According to (10), the proportions of clusters among different rings can be acquired and the proportion of clusters in the first ring is the most. Consequently, make sure that the number of clusters in the first ring reaches the maximum, which contributes to maximize the total number of clusters under Constraint (10). When all sensor nodes in the second ring become CH, the number of clusters in the first ring is not enough to satisfy Constraint (10) even though all the sensor nodes in the first ring become CH. In general, all conditions and constraints can be satisfied only if the sensor nodes in the first ring all become CH.

V. Energy-Balanced Unequal Clustering Approach (EBCA)

Based on the analysis above, the number of clusters and that of CHs in different rings can be obtained. In this section, the Energy-Balanced unequal Clustering Approach (EBCA) is presented. Similar to most of the clustering mechanism, EBCA is performed with a time unit of round which is a complete process consisting of cluster formation and data acquisition. Specifically, it primarily includes three phases: cluster formation phase, data forwarding phase, and cluster maintenance phase respectively.

A. *Cluster formation phase*

In this phase, the cluster can be determined and the CH needs to be selected from each cluster subsequently.

In the initialization phase, the Sink sends control messages to all the sensor nodes. Once receiving the control message, the node can determine the width of the ring r where it locates. Based on the width of each ring and the position of itself, each node can obtain the information concerning the ring it locates. For example, establish a Cartesian coordinate with the Sink location as the origin. If its coordinate is (x, y), then the node lies in the $\left\lceil \sqrt{(x^2 + y^2)} / r \right\rceil$th ring. The clusters in different rings are determined after the deployment of sensor nodes. Consequently, the nodes are grouped into clusters according to the ring where they locate.

In the phase of CHs selection, an optimal CH is selected within each cluster based on the analysis above. There are many kinds of measurement factors during the process of CH selection. In this paper, the selection of CHs only takes the energy and the position of current nodes into account. As mentioned in [37], a CH near the center of cluster can reduce the energy consumption by 15% compared with other situations. Because the initial energy of sensor node is the same, only the relative position with other nodes in the cluster is considered. The nodes in the same cluster can obtain the average distance to other nodes. Compared the relative distance with other nodes, the node which locates at the center of all nodes in the same cluster can be elected as a CH. Once the CH has been determined, it broadcasts a confirmation messages to its cluster members. The cluster members reply to the CH on receiving the confirmation message. Once the cluster is formulated, it never changes until the termination of network lifetime.

B. *Fuzzy logic in CH rotation*

To select the appropriate CH in the next round, the fuzzy logic is adopted in this paper. To be specific, the residual energy and relative distance with other nodes in a cluster are adopted as the input variables and the possibility of acting as CH is the only output of the fuzzy system (as shown in Fig. 3).

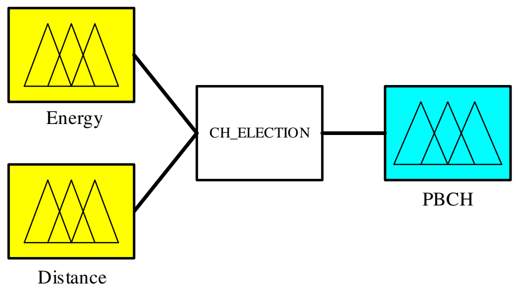

Fig. 3. Fuzzy System for selecting the next CH.

The first input of this system is the residual energy of sensor nodes. The membership functions of Low, Medium, High specify the low energy, intermediate energy, and high energy respectively. For the sake of convenience, the membership function of each other is presented as shown in Fig. 4.

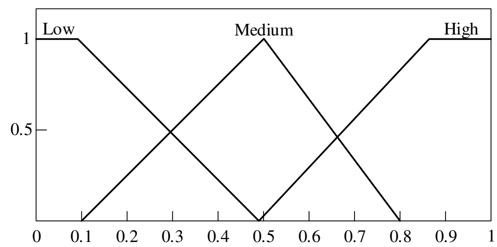

Fig. 4. The membership function of the residual energy.

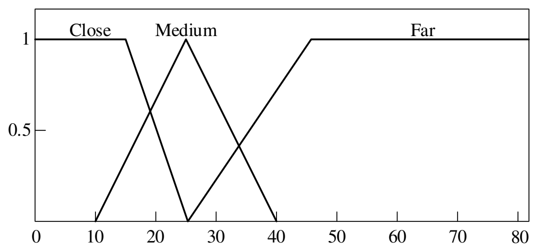

Fig. 5. Membership functions of the relative distance

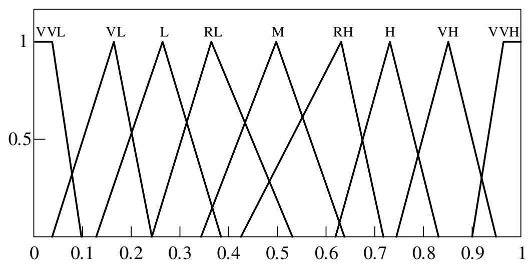

Fig. 6. Membership functions of the possibility of acting as the CH.

The second input of this system is the relative distance for other nodes in the same cluster. When the relative distance of current nodes is small, medium, and big, the value of membership functions will be marked as Close, Medium, and Far respectively. Fig. 5 shows the fuzzy membership functions which define the relative distance. Similarly, Fig. 6 presents the membership function of the language variables for the output of the fuzzy system.

The only output is the possibility of becoming CH (PBCH). For PBCH, the fuzzy membership function is presented in Fig. 6. In addition, the if-then rules of the fuzzy system for CH selection is listed as shown in Table II.

TABLE II

FUZZY IF-THEN RULES FOR CHS SELECTION

Energy	*Distance*	*PBCH*
Low	Close	L
Low	Medium	LW
Low	Far	VVL
Medium	Close	H
Medium	Medium	RH
Medium	Far	RL
High	Close	VVH
High	Medium	VH
High	Far	M

C. *Data forwarding phase*

The data forwarding phase includes intra-cluster data transmission and inter-cluster data forwarding.

During the first phase, the CMs propagate the data to the CH within the same cluster. During the simulation, the width of rings varies, which makes sure each CM communicates with its CH in one hop.

In the second phase, the CHs in the outer rings select out the best next hop from the next adjacent ring. The CHs in the first ring will send all of their packets to the Sink directly. During the process of next hop selection, both of the energy of next CH and the distance from current CH to next hop CH are taken into account simultaneously. In general, the CHs will select the CH with higher residual energy and smaller distance from itself to the current CH concurrently as the next hop.

D. *Cluster maintenance phase*

The mechanism of cluster head rotation is essential to ensure energy balance within each cluster. In general, the condition to trigger CH rotation is of great significance. Reference [30] defined the threshold of CH power as T (15% of initial energy). The rotation of CH starts when the residual energy of a CH is under T. In general, T will be tiny when the residual energy of nodes is too small. If the rotation of CHs starts late, this node will fail to perform any functions soon. In this paper, we adopt the threshold f which was utilized in Reference [31]. To be specific, $f = T \times E_{avg}$, where T is a factor controlling the frequency of rotation, and E_{avg} is the average residual energy of CMs in current cluster. Because E_{avg} constantly changes during the process of network function, f will adapt to the current real-time instead of keeping stationary. Therefore, the threshold f is more appropriate for the network which dynamically changes. According to Reference [31], the optimal value of T is 0.5. When the residual energy of CH is under f, the role of CH needs to rotate. Firstly, the CH will send the rotation control message to its CMs. Once receiving the packet, the CMs transmit their own residual energy and relative position within the same cluster to the CH. Subsequently, CH selects out the next CH based on the fuzzy logic in Section V.

VI. SIMULATION AND EVALUATION

In this section, we conduct extensive simulations to evaluate the energy efficiency of our proposal. To be specific, we carry out a lot of simulations with regard to a network consisting of homogenous sensor through MATLAB. Similar to Reference [33], the related simulation parameters are listed as shown in Table III.

TABLE III

SIMULATION PARAMETERS

Parameters	*Value*
Sink location	(0,0)
Initial energy	0.15-0.3J
E_{elec}	50nJ/bit
E_{amp}	0.659$nJ/bit/m^2$
n	5
R	60m
α	2
N	300
Upper boundary of round	600
Date packet size	1500$bits$
Control packet size	200$bits$

As shown in Table III, the network is composed of 300 sensor nodes and all the nodes are deployed randomly in a circle, with the radius of 60*m*. The size of data packets is set to be 1500*bits*. According to Reference [5], the transmission model of each node follows the free space model, which means the path loss exponent is equal to 2 (α=2). Fig. 7 shows the distribution of sensor nodes and the corresponding rings in the network topology. To evaluate the performance of our proposal objectively, the classic clustering algorithms LEACH, OCCN and EEFUC are adopted for comparisons in this paper.

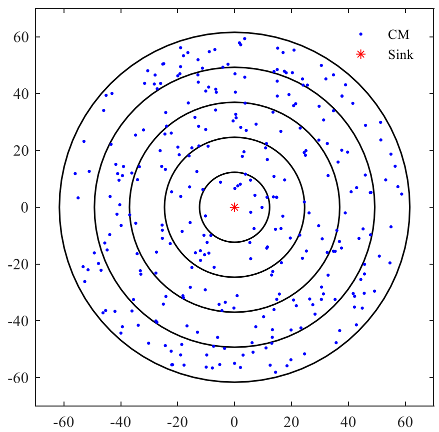

Fig. 7. Node distribution in the circular network of this paper.

Fig. 8 illustrates the energy consumption of CHs in different rings. it shows the amount of average energy consumed by CHs in one round. As shown in Fig. 8, the energy consumption of CHs in EBCA is more balanced compared with other three protocols. Consequently, the “Hot Spot Problem” can be effectively alleviated in EBCA. As a result, the network lifetime can be extended accordingly.

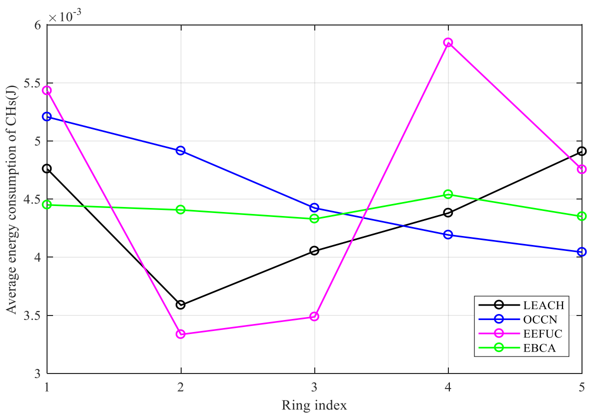

Fig. 8. Average energy consumption of CHs in each ring.

The number of packets received by the Sink is regarded as an indicator for the throughput. Therefore, the average number of packets by the end of simulation is counted and compared. As shown in Fig. 9, the difference among four algorithms in each round is not obvious. The average number of packets in LEACH is the most, which is about fifteen packets more than that of EBCA. The average number of packets in OCCN is almost the same with that of EBCA. The average number of packets in EEFUC is the least. Because the network lifetime of EBCA is the largest, the corresponding average number of packets is not the most.

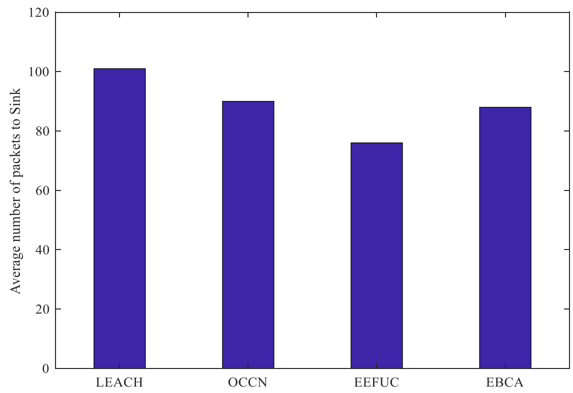

Fig. 9. Average number of packets to the Sink.

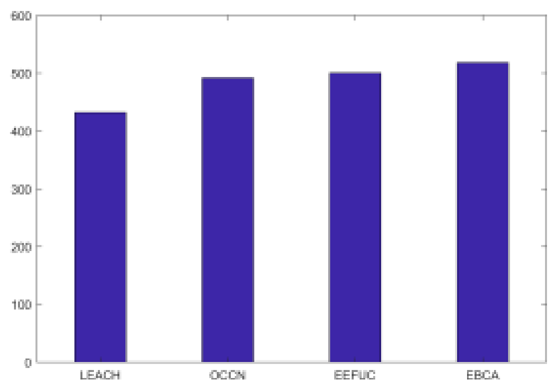

Fig. 10. Comparisons on energy efficiency among different algorithms.

Fig. 10 shows the energy efficiency of different algorithms. As stated in Reference [3], the energy efficiency is the ratio of amount of valid data transmitted to the Sink to the energy consumed. As shown in Fig. 10, the energy efficiency of EBCA is the highest, which means it is able to acquire the most amount of data when the energy consumption is the same. On the contrary, the energy efficiency of LEACH is quite different from other algorithms.

Fig. 11 presents the average residual energy of sensor nodes for each algorithm. Because the average number of packets to the Sink in EEFUC is the least, its average residual energy of the nodes is relatively higher than others. The residual energy of EBCA is similar to OCCN. With the increasement of rounds, it is obvious that the average residual energy in LEACH is much lower than those of three other protocols.

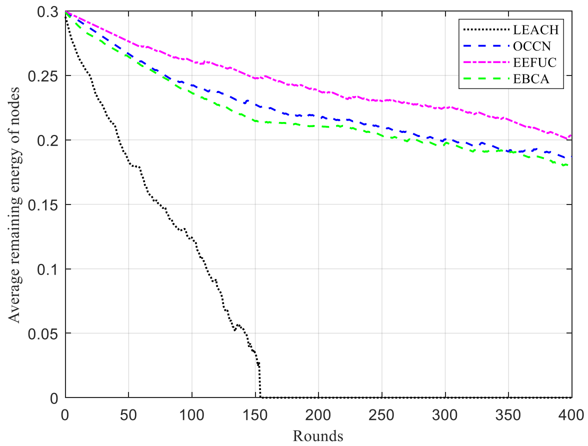

Fig. 11. Average residual energy of nodes over time.

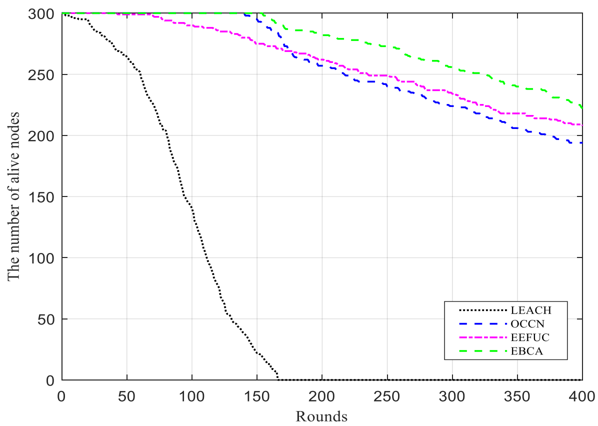

Fig. 12. The number of alive nodes over time.

The number of alive nodes is compared among four algorithms as shown in Fig. 12. The change of curve reflects the alive nodes in different protocols with the increasement of rounds. The transmission pattern of data packets in EBCA is hop-by-hop mode, and it is the same with other three protocols for accurate comparison. As shown in Fig. 8, the speed of nodes' death in EBCA is much slower than that in LEACH. Compared with the OCCN and EEFUC, the number of nodes alive in EBCA is the largest in the same round. When all of the sensor nodes in EBCA are dead, less than a third of the sensor nodes exhausted their energy. The result is consistent with the analysis in Section IV, which means our proposal plays an important role in reducing the overall energy consumption and extending the network lifetime.

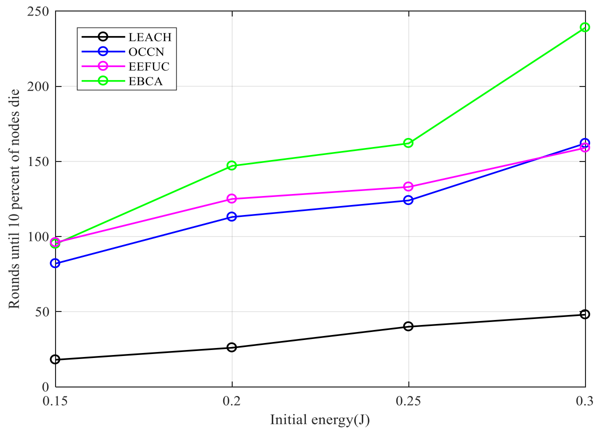

Fig. 13. The number of rounds until 10 percent of nodes died with different initial energy.

In order to compare the energy efficiency of our proposal with others under different scenarios, two groups of controlled trials with controllable variable are conducted. The initial energy of sensor nodes is changed and the number of rounds until 10 percent of nodes die are accounted. On the basis of the data obtained in different scenarios, the comparisons can be made as shown in Fig. 13. It indicates that the number of rounds when 10 percent of nodes die in EBCA is later than those of other three. As the initial energy of nodes increases, the disparity of round when 10 percent of nodes died among EBCA and other three algorithms keeps growing.

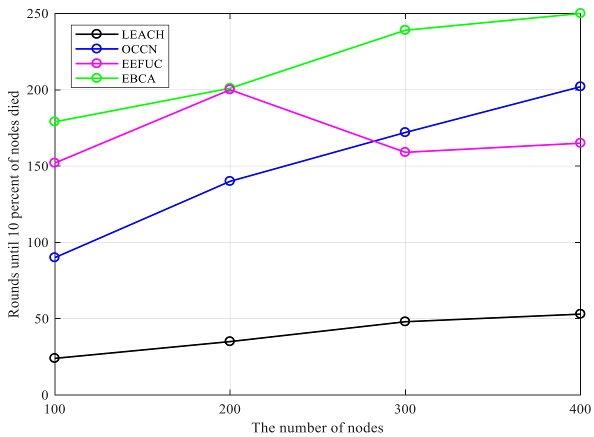

Fig. 14. The number of rounds until 10 percent of nodes died with different number of nodes.

Similar to Fig. 13, the number of nodes is changed in the network topology. Fig. 14 shows that the round when 10 percent of nodes die in EBCA is later than those of others as well. When the number of nodes is less, the nodes distributed in the first ring is less, which results in the drastic reduction in the number of CHs in the network topology. Consequently, the energy efficiency and network performance of EBCA degrades substantially when the number of CHs declines.

VII. CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

WSNs face severe challenges because of the finite supply of batteries. In this paper, we proposed an energy-balanced clustering algorithm to improve energy efficiency and extend the network lifetime accordingly. We obtained the optimal number of clusters in different rings of the network topology via detailed mathematical calculation and theoretical analysis. At the same time, the best next hop and a new CH can be selected in a controllable way based on the fuzzy logic, which helps to reduce and balance the energy consumption in both intra-cluster and inter-cluster communications. Besides, simulation results proved that EBCA can effectively improve energy efficiency and extend the network lifetime compared to the classic and latest clustering algorithms.

Our proposal can be applied in scenario where the distribution of sensor nodes follow uniform distribution. In general, the sensor nodes are usually randomly deployed or scattered with the consideration of practical demands. Meanwhile, the data between different rings often include a lot of redundancy, which leads to a waste of energy. Therefore, the number of nodes in the first ring plays an important role in EBCA. With the reduction in the number of nodes in the first ring, CHs in the network will be not enough to alleviate the "Hot Spot Problem". Therefore, our future work will focus on the alleviation of data redundancy in transmission. Besides, the research on the green IoT is of great importance for the applications of IoT. The technique of Simultaneous Wireless Information and Power Transfer (SWIPT) is potential to provide a solution for the energy problem in WSNs [38]. Therefore, we will also pay attention to the green IoT [39] and the SWIPT-based wireless sensor networks in our future research.

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