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A Heterogeneous Nodes-Based Low Energy Adaptive Clustering Hierarchy in Cognitive Radio Sensor Network

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ABSTRACT In order to cope with the resource shortage problem brought by cognitive radio technology in cognitive radio sensor network (CRSN), a new CRSN called heterogeneous CRSN (HCRSN) is proposed, where cognitive nodes (CNs) and sensor nodes (SNs) are separated and undertake different functions. Different from the existing clustering algorithms for homogeneous nodes based WSN, the clustering algorithm for HCRSN needs to consider the distribution of CNs among clusters such that enough high channel detection probability of each cluster can be guaranteed by the lowest deployment cost. Therefore, this paper first proposes a heterogeneous nodes based low energy adaptive clustering hierarchy (HLEACH) algorithm. In the algorithm, the sink node first updates the global information including the optimal number of clusters and average cluster radius and then broadcast it. Each CN calculates its competition radius after receiving the broadcasting information, and then start the competition for CHs based on the proposed competition rules. The elected CHs are finally censored targeting the optimal number of clusters to optimize the distribution of final CHs. In clusters' formation stage, non-CH CNs and SNs synthetically consider the distance and the connection degree of CHs such that the distribution of CNs among clusters and the energy consumption among CHs can be energy-efficiently balanced. The simulation results show that the proposed algorithm can not only effectively balance the distribution of CNs among clusters, guaranteeing enough high channel detection probability of each cluster and network energy utilization, but also balance the energy consumption among CHs, eventually prolong the network lifetime. Finally, the optimal deployment proportion of numbers and initial energy of the two types of nodes is also theoretical derived to maximize the energy utilization efficiency (i.e. the ratio of the network lifetime to the deployment cost).

INDEX TERMS WSN, CRSN, heterogeneous CRSN, clustering algorithm, cooperative spectrum sensing.

I. INTRODUCTION

Wireless sensor network (WSN) generally operates over the unlicensed public spectrum band, e.g. Industrial, Scientific and Medical (ISM) spectrum band. With the rapid growth of wireless new services, the unlicensed spectrum band becomes increasingly crowded [1]. This makes the communication performance of WSN sharply drop, which greatly affects the further development of WSN.

In order to address the spectrum congestion problem over the unlicensed spectrum band, some researchers propose to equip the sensor nodes (SNs) with the cognitive radio (CR) such that they have the spectrum sensing (SS) capability. The WSN with SS capability is referred to as cognitive radio sensor network (CRSN) [2]. Due to the introduction of CR technology, CRSN can opportunistically operate over the idle licensed spectrum by means of dynamic spectrum access technology, which can greatly increase the throughput and decrease the transmission delay [2]–[4].

Although the CR technology brings CRSN many benefits, it also increases the energy consumption of the nodes and thus requires nodes to have more powerful computational capability, which leads to the sharp increase of the CRSN deployment cost. In order to deal with the challenges caused by the introduction of CR technology, we propose to separate the cognitive functions from the cognitive sensor

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nodes (CSNs), thereby forming a type of independent nodes called cognitive nodes (CNs). The WSN consisting of CNs and SNs is also referred to as heterogeneous nodes based CRSN (HCRSN) in the paper.[1] In the HCRSN, since CNs are used for SS, they are required to have more energy and more powerful computational capability than SNs. This makes CNs more expensive than SNs, but comparable to CSNs. However, CNs can be deployed according to a small proportion in the total numbers of nodes since they don't participate in the data sensing. In addition, ordinary SNs need less energy and lower computational capability than CNs since they are only used for data sensing. This makes SNs much cheaper than CSNs and CNs. Therefore, compared with CRSN, HCRSN have the advantage of lower deployment cost.

In a HCRSN with very large deployment area, the data sensed by some SNs far from the sink node has to be forwarded to the sink node through multi-hop, the multi-hop HCRSN is thus formed. Clustering has been proved to be an effective way to prolong the lifetime in a traditional multi-hop WSN. Especially in HCRSN, where CNs and SNs are separated by each other and undertake different functions, CNs and SNs are required to closely coordinate for the data transmission. Furthermore, cluster structure can greatly facilitate cooperative SS (CSS) in multi-hop HCRSN, which is required to guarantee enough high channel detection probability. Therefore, forming two level clustering hierarchy topology structure by partitioning CNs and SNs into different clusters is the prerequisite and basis of the normal operation of the multi-hop HCRSN. The clustering routing algorithm is thus one of the key technologies to implement HCRSN, and it has extremely important practical significance for HCRSN deployment.

Since WSN generally operate in a harsh environment, it is very difficult to manually replace the energy-limited battery in nodes. The energy-efficient clustering routing protocol is thus required to prolong the network lifetime [5]. On the one hand, the existing clustering routing algorithms for WSN mainly focus on the minimization of the energy consumption of nodes, they do not consider SS and spectrum management issues [6]–[8], [14], [17], [18], [23]. On the other hand, CSNs in the traditional CRSN are homogeneous (cognitive function is integrated into the SNs) and they are often deployed in very considerable numbers, and thus there is no need to balance the distribution of CNs among clusters in their clustering algorithm [9]–[13], [15], [16], [24]. Therefore, the existing clustering algorithms for homogeneous nodes based WSN and CRSN can not be applied to HCRSN.

In view of the aforementioned facts, taking into account the heterogeneity of nodes in HCRSN, this paper proposes a heterogeneous nodes based low energy adaptive clustering hierarchy (HLEACH). In the algorithm, the sink node first updates and broadcasts the global information such as the optimal number of clusters and average cluster radius, and then CNs calculate their selves competition radii based on the deployment density of CNs, followed by the competition of CHs based on the proposed competition rules in the paper. The elected CHs are finally censored targeting the optimal number of clusters to optimize the distribution of final CHs. In the clusters' formation stage, non-CH CNs synthetically consider the distance to CHs and the connection degree of CHs regarding CNs such that the distribution of CNs among clusters can be energy-efficiently balanced. Apart from the distance to CHs and the connection degree of CHs regarding SNs, SNs also consider the distance between CHs and the sink node such that the energy consumption among CHs can be energy-efficiently balanced. Finally, to maximize the energy utilization efficiency, i.e. the ratio of the network lifetime to the deployment cost, the optimal deployment proportion of numbers and initial energy of the two types of nodes is also theoretical derived.

A. RELATED WORK AND MOTIVATION

Literature [19] first proposes HCRSN conception. In the proposed HCRSN, CNs are responsible for SS and SNs for data sensing, and the sensed data by SNs is directly transmitted to the sink node over the available channel detected by CNs. However, the literature cannot consider the clustering problem in the HCRSN since the proposed HCRSN in the literature is only a very simple single-hop model where the sink node act as the coordinator of all nodes. In practical application scenarios, nodes including CNs and SNs may be deployed in a large area, some of which may be far from the sink node. The sensed data by them has to be forwarded to the sink node through multi-hop, the multi-hop HCRSN is thus formed.

The literatures [25], [26] proposed dynamical spectrum allocation algorithms for heterogeneous cognitive radio networks, and the literature [27] used the deep reinforcement learning to select the modulation and coding schemes in cognitive HetNets. However, the "heterogeneity" in the references refer to the different cognitive radio users, e.g. multiple femtocells and WLANs in [25], while the "heterogeneity" in our work refer to the separate nodes in wireless sensor network, i.e. cognitive nodes and sensor nodes. Furthermore, the research target is different between the references and our work. The research target of the former is to allocate resource such as and spectrum and power in heterogeneous cognitive radio environment, and that of the latter is the clustering in the heterogeneous CRSN.

The low energy adaptive clustering hierarchy (LEACH) [14] is considered as the most representative algorithm. In the protocol, each node can be selected as a CH with a certain probability per round, and the task of being a CH is rotated among nodes. At the data transmission phase, each CH sends the aggregated data packet to the sink node through single hop.

In literature [23], a heterogeneity-aware Stable Election Protocol (SEP) is proposed to prolong the time interval before

[1] The conception is also mentioned in the literature [19], but its purpose is totally different from our work.

the death of the first node (stability period). SEP is based on weighted election probabilities that nodes become CHs according to their residual energy. However, the heterogeneity discussed in the literature merely refers to the difference in the initial energy, i.e. the nodes are still homogeneous except their initial energy. In contrast, the heterogeneity in HCRSN is not limited to the difference in the initial energy, it still includes the difference in their undertaken functions (CNs are responsible for SS and SNs for data sensing). Therefore, the algorithm proposed by the literature cannot be applied to HCRSN.

In literature [24], a novel energy efficient distance-based clustering and routing algorithm using multi-hop communication approach is proposed. Based on the distance, the heterogeneous CR based WSN are divided into different regions and are allocated with a unique spectrum. However, as in literature [23], the heterogeneity considered in the literature merely refers to the difference in the initial energy, i.e. the nodes are still homogeneous except their initial energy. The proposed clustering algorithm in the literature cannot be applied to the HCRSN.

In literature [17], a hybrid, energy-efficient, distributed clustering approach (HEED) is proposed to extend LEACH by considering the constraints on communication range and the information of intra-cluster communication cost. It coordinates election process to select SNs with more neighbors and larger residual energy as CHs. In the HEED, the main parameter is the residual energy of the nodes, the secondary parameter is the number of adjacent nodes. The HEED protocol thus has significant improvements in lifetime and throughput compared to LEACH.

In literature [18], a non-uniform size clustering method (EEUC) is proposed to balance the energy consumption of CHs. Its basic idea is to form a multi-hop non-uniform clustering network according to the geographic location of CHs. The proposed method can make the coverage area of the cluster follow a certain trend, that is, the closer the cluster is to the sink node, the smaller the coverage area of the cluster and further reduces the energy consumption of CHs used for data aggregation in the clusters. This enables CHs near the sink node to use more energy to forward data, and further balance the energy consumption among CHs. The proposed algorithm can thus effectively solves the hotspot problem in WSN.

The literature [11] proposed a cognitive LEACH (CogLEACH) for CRSN. In the protocol, the number of vacant channels detected by nodes is used as a weight in the probability that each node becomes a CH during the CHs election process. The more the number of available channels detected by nodes, the greater the probability that nodes have the same channel as the surrounding nodes, and the easier it forms a cluster. Thus the nodes with more vacant channels can be elected as CHs with a higher probability.

The literature [13] proposed a distributed spectrum aware clustering scheme (DSAC) for CRSN. In the scheme, the communication power model for CRSN consists of intra-cluster aggregation and inter-cluster relaying. After deriving the optimal number of clusters, the groupwise constrained clustering algorithm is proposed to minimize the energy consumption of CRSN, in which the spectrum-aware requirement is regarded as groupwise constraint.

The literature [15] proposed an event-driven clustering algorithm (ESAC). When an event is detected, SNs between the event occurrence point and the sink is activated as a qualified nodes. The CHs are selected among the qualified nodes according to their connection degree, the number of available channels and the distance to the sink node. The CHs maximize the number of two-hop neighbor nodes by selecting single-hop members to increase inter-cluster connectivity. The clusters can only generated between the event occurrence point and sink node, and the clusters are dismissed after the end of the event, thereby reducing the unnecessary formation and maintenance costs of clusters and finally greatly reducing energy consumption.

SCEEM [16] is a routing algorithm suitable for multimedia networks. In SCEEM, the optimal number of clusters is derived to minimize quality distortion due to packet loss and latency in multimedia transmissions. Under the premise of determining the number of CHs, CHs are selected according to the residual energy and SS results.

The literature [20] analyzed the problem about how to form a stable cluster in Cognitive Radio Ad Hoc Networks (CRAHN), and proposed a description of the robust clustering problem. The problem is proved to be NP-hard problem, and then the centralized solution is also proposed. Meanwhile, the authors also propose a distributed solution to adapt to the dynamics of ad hoc cognitive radio networks.

The literature [21] proposed a cluster-based architecture to allocate different control channels in various clusters. The clustering problem is formulated as a bipartite graph problem, where a class of algorithms is developed to provide different tradeoffs between the number of common channels in a cluster and the cluster size. Clusters can thus guaranteed to have a desirable number of common control channels without the need for frequent reclustering.

As can be seen from the aforementioned discussions, the clustering algorithms proposed in the literature [14], [17], [18], [23] can be only applied to WSN. The clustering algorithms proposed in the literature [11]–[13], [15], [16], [20], [21], [24] take into account the feature of cognitive function in WSN. However, all the algorithms can be only applied to homogeneous nodes based CRSN where the cognitive function is integrated on sensor nodes, thus they can not be applied to HCRSN.

To address the challenge brought by the heterogeneity of nodes in HCRSN in the clustering process, this paper proposes the HLEACH.

B. THE MAIN CONTRIBUTION

The main contributions of the paper can be summarized as follows.

- The paper first proposes the HCRSN to cope with the resource shortage problem brought by CR in CRSN, which consists of CNs with more initial energy and more powerful computational capability and ordinary SNs. In HCRSN, the two types of nodes undertake different functions, and they can be deployed according to a certain proportion of numbers and initial energy to reduce deployment cost. Furthermore, in the proposed HCRSN, cluster structure based data transmission method and the work time sequence of nodes are also proposed.
- The paper first proposes HLEACH. In the proposed HLEACH, there are the following several contributions. (i) Based on the proposed work time sequence of nodes in the HCRSN, the paper derives the optimal number of clusters that can minimize the network energy consumption on the premise of guaranteeing enough high channel detection probability of each cluster. (ii) The paper proposes a node-density based determination method of the competition radius. (iii) The paper proposes an iterative censoring method to optimize the distribution of final CHs. (iv) The paper proposes an energy-efficient balance method where the distance and connection degree are synthetically considered in the clusters' formation stage.
- The optimal deployment proportion of numbers and the initial energy of CNs and SNs is theoretically derived to maximize the energy utilization efficiency, i.e. the ratio of the network lifetime to the deployment cost.
- A large number of simulation experiments are done to prove the effectiveness of the proposed HLEACH. The results show that the proposed algorithm can not only energy-efficiently balance the distribution of CNs among clusters, guaranteeing enough high channel detection probability and energy utilization, but also energy-efficiently balance the energy consumption among CHs, eventually prolong the network lifetime.

The rest of this paper is organized as follows. The section II introduces the preliminaries including network model (Section II.A) and energy consumption model (Section II.B). The section III introduces the proposed clustering algorithm, which includes the determination of the number of clusters in Section III.A, the determination of CHs in Section III.B, the clusters' selection of Non-CH CNs in Section III.C, the clusters' selection of SNs in Section III.D, the stabilization phase in Section III.E and the adaptiveness of the clustering algorithm in Section III.F. The section IV is the experimental results and analysis, which include the impact of weight coefficients on the distribution of CNs among clusters in Section IV.A, the impact of weight coefficients on the energy balance among CHs in Section IV.B, the average channel detection probability of clusters and network energy consumption in Section IV.C, the comparison of the balance of the energy consumption among CHs under different algorithms in Section IV.D, the comparison of the number of clusters under different algorithms in Section IV.E, the comparison of network lifetime in Section IV.F, the determination of the proportion of CNs in total numbers in Section IV. G, the determination of the initial energy ratio of CNs to SNs in Section IV. H, and the simulation snapshots of the proposed clustering algorithm in Section IV. J, followed by the conclusion, possible future plans and research issues in the final section.

II. PRELIMINARIES

A. NETWORK MODEL

We assume that K CNs and SNs are randomly deployed in a large area to periodically collect data from surrounding environment. The data sensed by the SNs far from the sink node has to be forwarded to the sink node through multi-hop, a multi-hop HCRSN is thus formed.

Clustering has been proved to be an effective way to prolong the lifetime in a traditional multi-hop WSN. Specially, in HCRSN, CNs and SNs are separated each other and undertake different functions, thus they must coordinate closely to complete the data transmission. Furthermore, cluster structure can greatly facilitate cooperative SS (CSS) in multi-hop HCRSN, which is required to increase the channel detection probability of each cluster. Therefore, forming two level clustering hierarchy topology by partitioning CNs and SNs into different clusters is the prerequisite and basis for the normal operation of the multi-hop HCRSN.

In the HCRSN, since CNs can be designed to have more power and more powerful computational capability than SNs, they are more suitable to act as CHs. Though they are more expensive than SNs, they can be deployed according to a small proportion in total numbers to reduce the network deployment cost. For example, there may exist a few CNs used for CSS and dozens of SNs used for data sensing in a cluster. The schematic diagram of the clustering for the HCRSN is shown in Fig. 1.

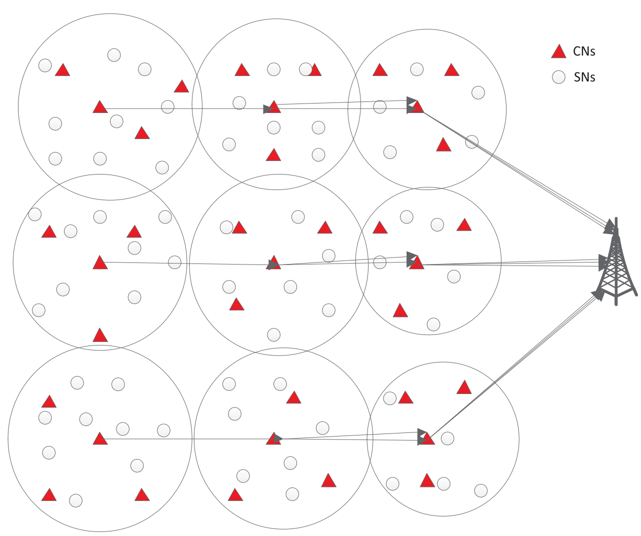

FIGURE 1. The schematic diagram of the clustering for multi-hop HCRSN.

In the paper, the following conditions are assumed:

- The sink node is located outside the monitoring area.
- Nodes are randomly and uniformly deployed, and they are all stationary after deployment.
- The monitoring area is square or quasi square.
- CNs have more initial energy and more powerful computational capability than SNs, and they can be deployed according to a small proportion in total number of nodes to reduce the deployment cost.
- CNs and SNs can obtain their coordinates in the network by means of the positioning algorithm such as three-point positioning algorithm.
- Each node can automatically adjust the transmit power according to the distance to its receiver.
- There is at least a common control channel (CCC) in the network.
- The distance based routing protocol is used between CHs during the data relay in the multi-hop HCRSN.
- The sensed data by SNs is transmitted to their CHs according to the allocated slot time over their detected channel in clusters, and a simple channel negotiation protocol between CHs is used during data relay, where the relay CHs wait the transmission from neighbors over the neighbor's channel until the data is received, and then start to relay the data over its own channel.
- The total time used for inter and intro-cluster transmission (including the waiting time) over the licensed channel in one round is short enough that the coexistence between the primary users and HCRSN is perfect based on CR technology.

In the paper, the fusion rule of the detected results by CNs is assumed to be OR, which can be generalized as "1-out-of-N" voting based decision fusion [22]. Under this rule, if at least one CN detects the presence of a primary user (PU), then the PU is considered as being present. Therefore, the joint detection probability of the T CNs are:

$$F_d = 1 - \prod_{T} (1 - p_d) \tag{1}$$

where p_d is the probability that one CN detects one channel to be busy when a PU exists.

B. ENERGY CONSUMPTION MODEL

The energy consumption model in radio consists of the transmitting mode and the receiving mode, which are shown in Fig. 2. In the transmitting mode, the transmitter consumes energy to run the radio electronics and the power amplifier. In the receiving mode, the receiver consumes energy to run the radio electronics. In the model, the energy loss can be divided into "free propagation" and "multi-path fading" transmission models. If the signal transmission distance is less than d_0, the transmission mode is "free propagation", i.e. the transmitting power is attenuated by d^2, where d is the distance between the transmitter and the receiver. If the signal transmission distance is greater than d_0, the transmission mode is "multi-path fading", i.e., the transmitting power is attenuated by d^4. Therefore, when L-bit data is transmitted, the energy consumed by the transmitter can be calculated as:

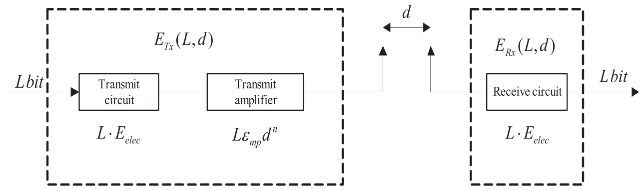

FIGURE 2. The energy consumption model in radio.

$$E_{Tx}(L, d) = \begin{cases} LE_{elec} + L\varepsilon_{fs} d^2 & d < d_0 \\ LE_{elec} + L\varepsilon_{mp} d^4 & d \geq d_0 \end{cases} \tag{2}$$

where E_{elec} represents the electronics energy, which depends on factors such as the digital coding, modulation, filtering, and spreading of the signal. ε_{fs} and ε_{mp} respectively represents the energy amplification factor under the free propagation and multi-path fading model, which depend on the distance to the receiver and the acceptable bit-error rate. d_0 is a threshold, and $d_0 = \sqrt{\varepsilon_{fs} / \varepsilon_{mp}}$.

The energy consumed by the radio receiver when the L bit data is received can be calculated as:

$$E_{Rx} = L \cdot E_{elec} \tag{3}$$

III. CLUSTERING ALGORITHM

A. DETERMINATION OF THE NUMBER OF CLUSTERS

In multi-hop HCRSN, the data collected by the SNs is first sent to their CHs, and then is forwarded to the sink node. Because the data collected by SNs in clusters has high redundancy, it is often fused into a fixed-length packet in their CHs. The work of CHs starts from CSS, and its work time sequence is in turn SS, the reception of the detected results of non-CH CNs, the decision and broadcast of available channels, the reception of the data collected by SNs, the data fusion and data relay, as shown in Fig. 3.

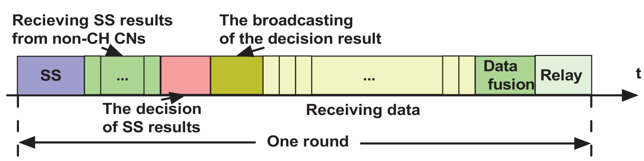

FIGURE 3. The work time sequence of CHs.

When the clusters are far from the sink node, the aggregated data by their CHs has to be forwarded to the sink node through multiple hops. According to the energy consumption model (2), when the distance between the transmitter and receiver is more than d_0, extra energy is consumed. Assuming that the distance from CHs to the next-hop CHs (relay node) is less than d_0, according to the work time sequence of CHs in Fig. 3 and the energy consumption model, the energy consumed by CHs in one round can be calculated as follows:

$$E_{CH} = ML_1 \cdot E_{elec} + NL_2 \cdot E_{elec} + ML_1 \cdot E_{DA} + E_{sense} + L_3 \cdot E_{elec} + L_3 \cdot \varepsilon_{fs} \cdot d_{toNEXT}^2 + L_4 \cdot E_{elec} + L_2 \cdot E_{elec} + L_2 \cdot \varepsilon_{fs} \cdot d_{toCH}^2 \tag{4}$$

where M represents the average number of SNs in clusters, L_1 represents the size of the data sensed by SNs, N represents the average number of non-CH CNs in clusters, and L_2 represents the size of the detected results by CNs, E_{DA} is the average consumed energy by CHs when fusing 1 bit data, d_{toNEXT} represents the average distance from CHs to the next-hop CHs, d_{toCH} represents the average distance between cluster members and their CHs, E_{sense} is the average consumed energy by CNs when detecting channels, L_3 denotes the average amount of data transmitted by CHs (including the fused data in their own clusters and the relay data from other clusters), and L_4 denotes the average amount of data received by the relay CHs.

Besides CHs, there are two types of cluster members in the clusters in the HCRSN, they are SNs and non-CH CNs, respectively.

- The SNs for data sensing.
  The SNs in turn transmit the sensed data to their CHs after receiving the broadcasting message about available channel from their CHs. It is assumed that there are enough numbers of CNs in each cluster[2], which can guarantee to provide enough high channel detection probability for each cluster that can satisfy the communication requirement of the network. Therefore, the consumed energy caused by data retransmission due to error channel detection is ignored. Assuming that the distance between SNs and their CHs is less than d_0, the energy consumed by SNs in one round can be calculated as follows.

$$E_{SN} = L_1 \cdot E_{elec} + L_1 \cdot \varepsilon_{fs} \cdot d_{toCH}^2 + L_2 \cdot E_{elec} \tag{5}$$

- The non-CH CNs for CSS.
  All CNs perform SS, and non-CH CNs transmit the detected results to their CHs over CCC. Assuming that the distance between non-CH CNs and their CHs is less than d_0, the energy consumed by non-CH CNs in one round can thus be calculated as follows.

$$E_{non-CH\,CN} = L_2 \cdot E_{elec} + L_2 \cdot \varepsilon_{fs} \cdot d_{toCH}^2 + E_{sense} \tag{6}$$

Let m denote the proportion of CNs in total numbers of nodes in the multi-hop HCRSN, and q the number of final CHs, then the average number of SNs in each cluster is $K(1-m)/q$, and the number of non-CH CNs in cluster is $(K \cdot m/q) - 1$.

Therefore, the average energy consumed by one cluster in one round can be calculated as

$$E_{cluster} = E_{CH} + \frac{K(1-m)}{q} \cdot E_{SN} + (\frac{K \cdot m}{q} - 1) \times E_{non-CH\,CN} \tag{7}$$

[2]The primary target of the clustering algorithm for HCRSN is to guarantee enough number of CNs in each cluster.

Due to the random and uniform distribution of nodes in the considered scenario, we can obtain

$$\begin{aligned} E[d_{toCH}^2] &= \iint (x^2+y^2)\rho(x,y)dxdy \\ &= \iint r^2 \rho\,(r,\theta)\, rdrd\theta \\ &= \rho \int_{\theta=0}^{2\pi} \int_{r=0}^{\sqrt{\frac{S}{\pi q}}} r^3 drd\theta \\ &= \frac{\rho S^2}{2\pi q^2} = \frac{S}{2\pi q} = \frac{H^2}{2\pi q} \end{aligned} \tag{8}$$

where $\rho(x, y) = 1/(S/q)$ is the node distribution, S represents the deployment area and $S = H^2$ due to the assumption of quasi square or square area.

The average communication distance of the one-hop relay, which approximately equals the average diameter of clusters, can be thus calculated as

$$d_{toNEXT} = 2\sqrt{\frac{S}{\pi q}} = \frac{2H}{\sqrt{\pi q}} \tag{9}$$

Assume H be the deployment width in the direction of the sink node, then the maximum number of hops from the farthest CHs to the sink node is

$$l_{tr}^{max} = \frac{H}{d_{toNEXT}} = \frac{H}{\frac{2H}{\sqrt{\pi q}}} = \frac{\sqrt{\pi q}}{2} \tag{10}$$

The minimum transmission times of the data is one, and the average transmission times of CHs in the network (including the transmission times of data relay from other cluster) can be calculated as folllows.

$$l_{tr}^{av} = \frac{l_{tr}^{max} + 1}{2} \tag{11}$$

In the paper, the redundant data aggregated by CHs is assumed to be fused into a fixed-size packet, whose size is assume to equal the size of the data sensed by SNs , i.e. L_1, then we can obtain

$$L_3 = l_{tr}^{av} \cdot L_1 \tag{12}$$

The average maximum number of relay times in the network can be calculated as (e.g. the CHs near the sink node)

$$l_{re}^{max} = l_{tr}^{max} - 1 \tag{13}$$

The remote CHs don't relay any data, so the minimum relay times is 0, then the average relay times of CHs in the network, which is also the average times that CHs receive data for relay, can be calculated by

$$l_{re}^{av} = \frac{l_{re}^{max} + 0}{2} = \frac{l_{tr}^{max} - 1}{2} \tag{14}$$

Therefore, $L_4 = l_{re}^{av} \cdot L_1$.

The total energy consumption of the entire network in one round can be written as

$$E_{round} = q \cdot E_{cluster} \tag{15}$$

It can be proved that the formula (15) is a concave function with respect to q (the proof refers to APPEDNDIX).

Taking the partial derivative of the formula (15) and making it 0, the optimal number of clusters can be calculated as follows.

$$q_{opt} = \left\lfloor \left(\frac{2H^2 K \varepsilon_{fs} \left((1-m) L_1 + mL_2 \right)}{3\pi^{\frac{3}{2}} L_1 E_{elec}} \right)^{\frac{2}{5}} + 0.5 \right\rfloor \quad (16)$$

where $\lfloor x + 0.5 \rfloor$ represents the closest integer to x, and the proof of the formula (16) refers to APPEDNDIX A.

B. DETERMINATION OF CLUSTER HEADS

1) THE SELECTION OF CLUSTER HEADS

In HCRSN, CNs and SNs are separated by each other, and they respectively undertake different functions. Since CNs can be designed to have more powerful computing power and more initial energy than ordinary SNs (even may be equipped with energy harvesting devices in CNs [19]), it is more reasonable for CNs to act as CHs than SNs. Due to the limited capability of single CN, the CNs in the clusters are required to use CSS method to detect the channels.

In CSS, too few CNs in clusters may lead to low channel detection probability, which cannot satisfy the communication requirement of the network. Furthermore, the low channel detection probability can lead to high collision probability of data transmission, and further increase the network energy consumption due to the increase of retransmission times. Therefore, increasing the number of CNs in clusters (this also means that more CNs need to be deployed in the HCRSN) can significantly increase the channel detection probability, and further reduce the collision probability of data transmission. However, too many CNs within one cluster cannot make the channel detection probability keep the continuous growth. Contrarily, they can lead to excessive energy consumption and extra deployment cost.

Therefore, CNs should be as uniformly as possible distributed among clusters such that each cluster in HCRSN can obtain enough high channel detection probability at the cost of the deployment of the smallest number of CNs. This can greatly reduce the network deployment cost due to the decrease of the number of CNs, and further improve the energy utilization efficiency.

Based on the idea, in the paper, we first propose the determination method of node-density based non-uniform competition radius for the candidate cluster heads (CCHs) such that there are roughly equal numbers of non-CH CNs in each cluster.

Definition 1 (Competition Radius): The competition radius of CCH S_i, denoted by R_{S_i}, is defined as the distance from the Yth nearest CNs to itself, where

$$Y = \frac{K \cdot m}{q_{opt}} - 1 \quad (17)$$

It can be seen from the definition that the size of the competition radius in densely deployed area is less than that in sparsely deployed area.

Definition 2 (Adjacent CHs Set): The adjacent CHs set of CCH S_i is defined as $S_{S_i} = \{S_j | d(S_i, S_j) \le R_{S_i}\}$.

Definition 3 (Competitor): All other CCHs in the adjacent CHs set of CCH S_i are referred to as the competitors of CCH S_i.

Competition Rule 1: In the adjacent CHs set S_{S_i}, only the CNs with $E_r^{S_i} \ge \overline{E_r}$ are eligible to become CHs, where $\overline{E_r}$ is the energy threshold, which equals the average residual energy of all CNs in last round. The energy threshold $\overline{E_r}$ is used to avoid selecting the CNs with low residual energy as CHs. That is to say, only CNs whose residual energy is higher than the average residual energy of CNs $\overline{E_r}$ in last round are eligible for CHs.

Competition Rule 2: In the adjacent CHs set S_{S_i}, if $E_r^{S_i} \ge \overline{E_r}$ and its connection degree $\theta_{cs}^{S_i}$ around them regarding SNs and CNs is the highest, i.e. $\max \left\{ \theta_{cs}^{S_j}, \ S_j \in S_{S_i} \right\} = \theta_{cs}^{S_i}$, then CCH S_i becomes CHs. Note that "around them" refers to the average cluster radius $\overline{R}_c$ rather than the competition radius for the fair competition, where $\overline{R}_c = \frac{H}{\sqrt{\pi q}}$.

Competition Rule 3: The CCH S_i can make its decision only when all its competitors with more residual energy and higher connection degree make their decisions.

After all nodes including CNs and SNs are deployed, they can calculate and exchange their selves coordinates, which are respectively represented by $p_{cn}(x, y)$ and $p_{sn}(x, y)$. Therefore, CNs can calculate the distance to other CNs and the connection degree regarding CNs and SNs based on the coordinates of nodes. After the initiation process finishes, all CNs become the CCHs and constructs their own adjacent CHs set S_{S_i}, and then the CCHs make their own decisions as to whether they become CHs according to the competition rule 1, 2 and 3. The competition algorithm for CHs is detailedly described in the algorithm 1.

2) THE CENSORING OF CLUSTER HEADS

Since there may exist the overlap area among the competition radius of different CCHs, the number of elected CHs is generally more than the optimal number of clusters we expect. Different from the traditional clustering algorithm, another important idea of the proposed HLEACH algorithm is that the clusters should be as uniformly as possible distributed in HCRSN. Therefore, optimizing the distribution of CHs by deleting some redundant CHs can contribute to balance the distribution of CNs among clusters, and further guarantee enough high channel detection probability of each cluster and reduce the energy consumption.

As can be seen from Fig. 4, the competition radius of CH2 overlaps with those of CH1 and CH3. Assuming that $E_r^{CH_l} \ge \overline{E}_r, l = 1, 2, 3, E_r^{S_j} \ge \overline{E}_r, j = 4, 5, 6$ and $\theta_{cs}^{CH2} < \theta_{cs}^{S_j} < \theta_{cs}^{CH_l}, l = 1, 3, j = 4, 5, 6$, CH1 and CH3 always make their decisions prior to CH2. When CN S_j within the competition radius of CH1 and CH3 receive the election message

Algorithm 1: The Competition Algorithm for CHs

Initialization or update: $p_{cn}(x, y)$, $p_{sn}(x, y)$, L_1, L_2, E_{elec}, ε_{fs}, d_0, δ, $\overline{E_r}$, m, K, S, and H;
step 1: Calculate q_{opt} and $\overline{R}_c$;
step 2: The sink node broadcasts the global information such as $\overline{E_r}$, $\overline{R}_c$ and etc;
step 3: All CNs become CCHs;
step 4: CCH S_i calculates R_{S_i} and $\theta_{cs}^{S_i}$ regarding CNs and SNs within $\overline{R}_c$;
step 5: CCH S_i forms S_{S_i} within R_{S_i};
step 6: Start to compete for CHs:
while $E_r^{S_i} < \overline{E_r}$ **do**
  CCH S_i quits the competition for CHs and broadcasts its quitting competition message to its competitors;
end
while $E_r^{S_i} \geq \overline{E_r}$ **do**
  repeat
    if $\max\left\{\theta_{cs}^{S_j},\ S_j \in S_{S_i}\right\} = \theta_{cs}^{S_i}$ **then**
      S_i becomes a final CH and broadcasts its election message to its competitors;
    else
      CCH S_i waits for the decisions of its competitors;
      while *CCH S_i receives the election message from its competitors* **do**
        it quits the competition for CHs and broadcasts a quitting-competition message;
      end
      while *CCH S_i receives the quitting-competition message from its competitor S_j* **do**
        $S_{S_i} = S_{S_i} \backslash S_j$;
      end
    end
  until *All CCHs make their decisions*;
end
step 7: Select and delete the redundant CHs;
All newly elected CHs send their local information such as their coordinates, R_{CH_i}, $E_r^{S_i}$ and etc. to the sink node (the number of current CHs q_c can be thus obtained) and the sink node calculates the number of the redundant CHs q_r according to the censoring rule;
repeat
  if $q_r < q_c - q_{opt}$ **then**
    $\omega = \omega + 1$ and recalculate q_r
  else
    $\omega = \omega - 1$ and recalculate q_r
  end
until $q_r = q_c - q_{opt}$;
The sink node broadcasts the censoring information of current ω, the q_r redundant CHs thus become ordinary non-CH CNs again and other CHs become the final CHs.

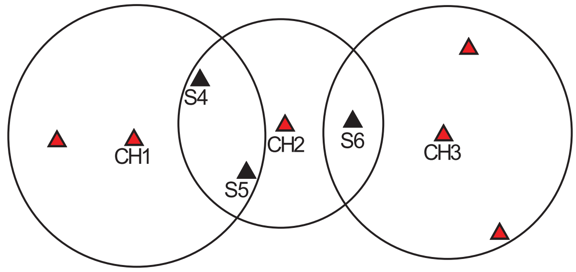

FIGURE 4. Schematic diagram of the redundant CHs.

from CH1 and CH3, they quit the competition for CHs and become their non-CH CNs. Therefore, when CH2 become a CH, there is no non-CH CNs for CSS in its cluster, which lead to very low channel detection probability in the cluster. This cannot satisfy the communication requirement of the network.

In order to avoid the occurrence of the above cases, the redundant CHs need to be removed to optimize the distribution of clusters (i.e. the location of CHs).

Censoring Rule: One of two CHs would be deleted and become the ordinary non-CH CN if the following censoring condition is satisfied.

$$\begin{cases} d(CH_i, CH_j) < R_{CH_i} + \omega * \delta \\ d(CH_i, CH_j) < R_{CH_j} + \omega * \delta \end{cases} \tag{18}$$

where $d(CH_i, CH_j)$ is the distance between CH_i and CH_j, ω is the adjustment factor, and δ is the step size.

The censoring algorithm of CHs is shown in step (8) in algorithm 1. It can be seen that the censoring algorithm is an iteration algorithm. The powerful computational capability of the sink node can greatly facilitate the execution of the algorithm. Note that δ can be designed to be small enough in the algorithm 1 such that $q_r = q_c - q_{opt}$.

C. THE CLUSTERS' SELECTION OF NON-CH CNs

When CHs receive the broadcasting message, some CHs become the final CHs, and other CHs become ordinary CNs again. The final CHs broadcast their election messages including their IDs, coordinates and the connection degree within the average cluster radius $\overline{R}_c$. When the non-CH CNs and SNs receive the election message from the final CHs, they start to perform their own clusters' selection algorithm.

In order to energy-efficiently balance the distribution of CNs among clusters, the distance between non-CH CNs and CHs and the connection degree of CHs regarding CNs (i.e. the number of nearby CNs) within the average cluster radius $\overline{R}_c$ are simultaneously considered when non-CH CNs choose clusters to join. Therefore, we propose to calculate the weighted summation of the two factors and select the cluster with the minimum value to join. The calculation formula of the weighted summation of the two factors corresponding to CH_i can be represented as

$$f_{CH_i}^C = w_{cd} p_{cd} d_{CH_i}^C + w_{cc} p_{cc} c_{CH_i}^C \tag{19}$$

where $d_{CH_i}^C$ is the distance between non-CH CNs and CH_i, and $c_{CH_i}^C$ is the connection degree of CH_i regarding CNs. w_{cd} and w_{cc} are the weighted coefficients corresponding to the two factors, respectively. Since $d_{CH_i}^C$ is generally much larger than $c_{CH_i}^C$, the balance factors p_{cd} and p_{cc} are added in the formula in order to enable both factors to exert significant influence on the clusters' selection. Considering the actual scenarios, $d_{CH_i}^C$ is generally 10 times larger than $c_{CH_i}^C$, thus $p_{cd}/p_{cc} = 1/10$ in the paper.

The clusters' selection algorithm of non-CH CNs can be summarized as follows.

Algorithm 2: The Clusters' Selection Algorithm of non-CH CNs and SNs

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Initiation: After CHs receive the broadcasting message, some CHs will become ordinary CNs again, and other CHs become the final CHs;
step 1: The final CHs broadcast their election messages including their ID, coordinates, connection degree and etc;
step 2: Non-CH CN S_i calculates the weighted summations of nearby CHs according to formula (19);
step 3: SNs calculates the weighted summations of nearby CHs according to formula (20);
step 4: Non-CH CN S_i select CH with the minimum value to join;
step 5: SNs selects the CH with the minimum value to join.

D. THE CLUSTERS' SELECTION OF SNs

When SNs wake up from sleeping according to their work time sequence and receive the broadcasting message from the final CHs, they start to perform their own clusters' selection algorithm.

In order to improve the energy utilization efficiency of SNs in data transmission, the distance between SNs and CHs is considered in the clusters' selection algorithm. In HCRSN, since the CHs near the sink node need to relay data from other CHs, they may consume more energy. Therefore, apart from the distance between SNs and CHs, we also consider the distance from CHs to the sink node and the connection degree regarding to SNs to balance the energy consumption among CHs.

Therefore, in order to energy-efficiently balance the the energy consumption among CHs, we proposed to calculate the weight summations of the three factors of nearby CHs and select CHs with the minimum value to join. The calculation formula of the weight summation of the three factors corresponding to CH_i can be represented as follows.

$$f_{CH_i}^S = w_{sd}p_{sd}d_{CH_i}^S + w_{sc}p_{sc}c_{CH_i}^S + w_{sk}p_{sk}\left(\frac{d_{sk}}{d_{CH_i}^{toBS}}\right) \quad (20)$$

where w_{sd}, w_{sc} and w_{sk} are respectively weight coefficients of $d_{CH_i}^S$, $c_{CH_i}^S$ and $d_{CH_i}^{toBS}$. $d_{CH_i}^S$ is the distance between SNs and CH_i, $c_{CH_i}^S$ is the connection degree of CH_i regarding SNs within the average cluster radius $\overline{R}_c$, $d_{CH_i}^{toBS}$ is the distance from CH_i to the sink node, and d_{sk} is the distance from SNs to the sink node. Since $\frac{1}{d_{CH_i}^{toBS}}$ is related to the location of CH_i and is always very little, it multiplies by d_{sk} to remain a relative constant value. p_{sd}, p_{sc} and p_{sk} is the balance factor, which are introduced to enable the three factors to have the significant impact on clusters' selection of SNs.

The clusters' selection algorithm of SNs is shown in algorithm 3.

E. STABILIZATION PHASE

- When the sensing time arrives, both CHs and non-CH CNs simultaneously detect the target channels.
- Non-CH CNs send their detect results to their CHs over CCC and then enter into the sleeping state.
- CHs make their decisions based on the aggregated detected results and broadcast the message including the decision result regarding available channels and allocated time slot to their SNs, and then wait to receive the sensed data by SNs.
- SNs receive the broadcasted message from their CHs and start to in turn send their sensed data to their CHs over the available channel according to the allocated time slot, and then enter into the sleeping state.
- CHs in turn receive the sensed data by SNs and start to fuse the aggregated data.
- CHs wait to receive the fused data from other CHs and then send the data to next CHs or the sink node.
- CHs enter into the sleeping state until the beginning of the next work cycle.

F. THE ADAPTIVENESS OF THE CLUSTERING ALGORITHM

In step 8 in algorithm 1, each newly elected CH sends its local information to the sink node before censoring the redundant CHs. The local information includes the current information of all CNs within the competition radius such as the residual energy, IDs of newly elected CHs and etc. Therefore, at the beginning of clustering in each round, the sink node can always obtain the current information of all CNs. It can thus calculate and broadcast the current global information such as the average residual energy and average cluster radius to all CNs, which can make the clustering algorithm adaptive.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The proposed algorithms are simulated by using MATLAB simulation tool. We assume 200 CNs and SNs to be deployed in the area of $200m \times 200m$, which can opportunistically operate over 5 licensed channels. The initial energy of the nodes is assumed to be $0.5J$. Other simulation parameters are shown in Table 1.

TABLE 1. The key notations.

Notation	Definition
E_{elec}	the electronics energy
ε_{fs}	the energy amplification factor under the free propagation
ε_{mp}	the energy amplification factor under the multi-path fading
L	the length of data
E_{CH}	the energy consumed by CHs in one round
M	the average number of SNs in clusters
L_1	the size of the data sensed by SNs
N	the average number of non-CH CNs in clusters
L_2	the size of the detected results by CNs
E_{DA}	the energy consumption of CHs when fusing 1 bit data
d_{toNEXT}	the average distance from CHs to the next-hop CHs
d_{toCH}	the average distance between CMs and their CHs
E_{sense}	the energy consumption of CNs when detecting channels
L_3	the average amount of data transmitted by CHs
L_4	the average amount of data received by the relay CHs
R_{S_i}	the competition radius of CCH S_i
S_{S_i}	the adjacent CHs set
$\overline{E_r}$	the energy threshold
$\overline{R}_c$	the average cluster radius
$p_{cn}(x, y)$	the coordinates of CNs
$p_{sn}(x, y)$	the coordinates of SNs

A. THE IMPACT OF WEIGHT COEFFICIENTS ON THE DISTRIBUTION OF CNS AMONG CLUSTERS

The non-CH CNs select the clusters with the minimum value to join according to the formula (19), which synthetically considers the distance between CNs and CHs and the connection degree of CHs regarding CNs within the average cluster radius $\overline{R}_c$. The weight coefficients w_{cd} and w_{cc} can impose great influence on the balance of the distribution of CNs among clusters. We use the variance of the number of CNs in clusters to represent the balance of the distribution of CNs among clusters. The smaller the value, the better the balance, and vice versa. Fig. 5 shows the impact of the weight coefficients on the distribution of CNs among clusters.

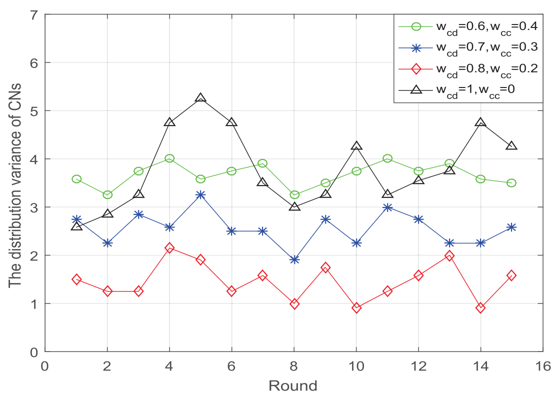

FIGURE 5. The impact of weight coefficients on the distribution of CNs among clusters ($p_{cd}/p_{cc} = 1/10$).

It can be seen from Fig. 5 that when $w_{cd} = 0.8$ and $w_{cc} = 0.2$, the variance value is the smallest, this is to say, the balance of the distribution of CNs among clusters is the best. This indicates that the appropriate weight allocation can help to balance the distribution of CNs among clusters.

It can be seen from Fig. 5 that in the special case of $w_{cd} = 1$ and $w_{cc} = 0$, i.e. the selection is completely dependent on the distance between CHs and CNs, the balance is good in some rounds, but it is very bad in some rounds (i.e. the stability is very poor). In another special case of $w_{cd} = 0$ and $w_{cc} = 1$, i.e., the selection is completely dependent on the connection degree (i.e. the number of CNs within the average cluster raius $\overline{R}_c$), all non-CH CNs always select CHs with the minimum connection degree, which can lead to the worst balance. Because the variance value under the case is much larger than that under other cases, it is not shown in the Fig. 5.

B. THE IMPACT OF WEIGHT COEFFICIENTS ON THE ENERGY BALANCE AMONG CHs

The SNs select the clusters with the minimum value to join according to the formula (20), which synthetically considers the distance between SNs and CHs, the connection degree of CHs regarding SNs within the average cluster radius $\overline{R}_c$ and the distance between CHs and the sink node. The weight coefficients w_{sd}, w_{sc} and w_{sk} can impose great influence on the balance of the energy consumption among CHs. We use the variance of the energy consumption of CHs to represent the balance of the energy consumption among CHs. The smaller the value, the better the balance, and vice versa. Fig. 6 shows the impact of weight coefficients on the balance of the energy consumption among CHs.

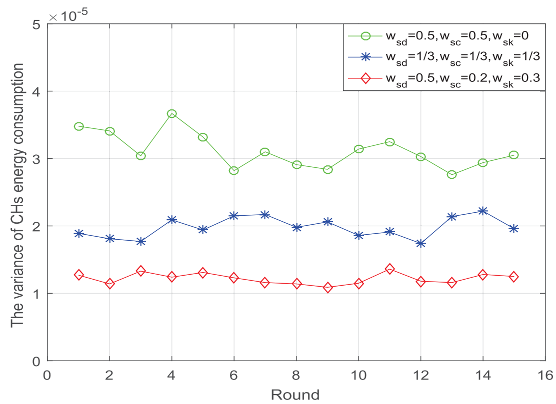

FIGURE 6. The impact of weight coefficients on the balance of the energy consumption among CHs ($p_{cd}/p_{sc}/p_{sk} = 1/1/30$).

It can be seen from Fig. 6 that when $w_{sk} = 0$, i.e. the distance from CHs to the sink node is not considered, the balance of the energy consumption among CHs is the poorest. When three kinds of factors are simultaneously considered, the balance can be improved. It can be seen from Fig. 6 that when $w_{sd} = 0.5$, $w_{sc} = 0.2$ and $w_{sk} = 0.3$, the balance of the energy consumption among CHs is the best. This indicates that the appropriate weight allocation can help to balance the energy consumption among CHs.

C. AVERAGE CHANNEL DETECTION PROBABILITY OF CLUSTERS AND NETWORK ENERGY CONSUMPTION

To the best of our knowledge, there are not clustering algorithms for HCRSN in existing literatures. To more deeply understand the performance of the proposed algorithm, we apply the idea of several representative clustering algorithms for WSN such as LEACH [14], EEUC [18] and CogLEACH [11] to HCRSN, and compare them with the proposed algorithm in the paper.

The modified LEACH algorithm, where the idea of LEACH is applied to HCRSN, is referred to as LEACH-G in the paper. In the LEACH-G, according to the idea of LEACH, CNs are selected as CHs with a predefined probability, and then the non-CH CNs and SNs select their nearest CHs to join.

The modified EEUC algorithm, where the idea of EEUC is applied to HCRSN, is referred to as EEUC-G in the paper. In the EEUC-G, according to the idea of EEUC, each CN first generates a random number, and then CNs with less number than the predetermined threshold T become CCHs. All CCHs form their own adjcent CHs sets within their competitive radii, which depends on the distance between the sink node and them, and then the final CHs are determined by the residual energy of the nodes. Non-CH CNs and SNs choose their nearest CHs to join.

The modified CogLEACH algorithm, where the idea of CogLEACH is applied to HCRSN, is referred to as CogLEACH-G in the paper. In the CogLEACH-G, according to the idea of CogLEACH, the number of vacant channels is used as a weight in the probability $P_i(t)$ that each node becomes a CH. Non-CH CNs and SNs select their nearest CHs to join.

Fig. 7 and Fig. 8 show the average channel detection probability of clusters and network energy consumption under the four algorithms in the randomly selected 15 rounds.

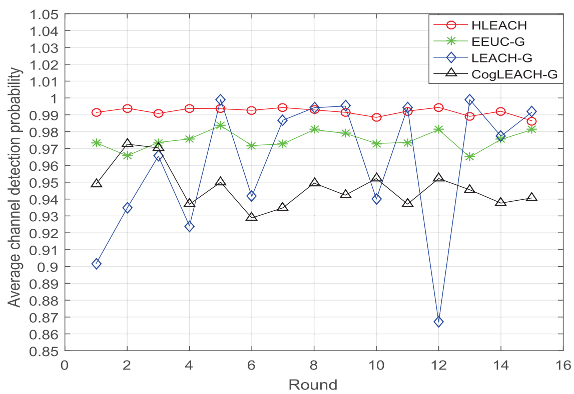

FIGURE 7. The average channel detection probability of clusters under different algorithms.

It can be seen from Fig. 7 that the proposed algorithm can provide a higher average channel detection probability than other algorithms in most rounds. In the 15 randomly selected rounds, the average channel detection probability under the proposed algorithm in 12 rounds is greater than 99%, and that in other 3 rounds approaches 99%. The proposed algorithm not only considers the distribution of CHs in HCRSN, but also the distribution of CNs among clusters, and thus it provides better balance in the distribution of CNs among clusters than other algorithms, which lead to higher and more stable channel detection probability of clusters.

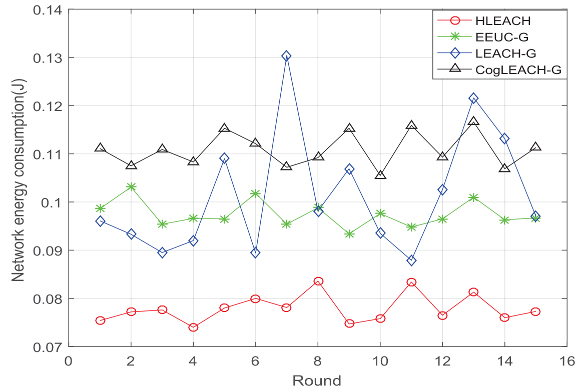

FIGURE 8. The network energy consumption under different algorithms.

The EEUC-G algorithm provides lower channel detection probability than the proposed algorithm in most rounds, but higher than CogLEACH-G. EEUC-G considers the distance between CHs and the sink node, and thus it provide more even distribution of CHs than CogLEACH-G. This can lead to better balance in the distribution of CNs among clusters, and further higher and more stable channel detection probability than CogLEACH-G.

Compared with other algorithms, the location of CHs under LEACH-G is the most random, it thus provides the most unstable channel detection probability of clusters among the algorithms.

Just because of the aforementioned reasons, it can be seen from Fig. 8 that the network energy consumption under the proposed algorithm is the least, and those under EEUC-G and CogLEACH rank second and third.

It can be observed from Fig. 7 and 8 that the average channel detection probability of clusters and network energy consumption under LEACH-G algorithm have a large fluctuation. This is because the selection of CHs has great randomicity in the LEACH-G algorithm. That is to say, the number of CHs produced in each round is not fixed. The number of CHs in some rounds is very small, and that in some rounds is very large. In the first case, the size of the clusters becomes very large. This may make the distance between the cluster members (CNs and SNs) and CHs become very large, and further lead to the increase of the energy consumption inter and intra the clusters. In the second case, the size of the clusters becomes very little. This may make the number of CNs in the clusters be far less than the number of CNs required by the detection threshold even there is only one CN (CH) in the clusters, and further lead to low channel detection probability of clusters, which cannot satisfy the communication requirement of the network, and which can lead to the increase of energy consumption intra the clusters due to the data retransmission.

D. THE COMPARISON OF THE BALANCE OF THE ENERGY CONSUMPTION AMONG CHS UNDER DIFFERENT ALGORITHMS

It can be seen from Fig. 9 that the proposed algorithm is the best in term of the balance of the energy consumption

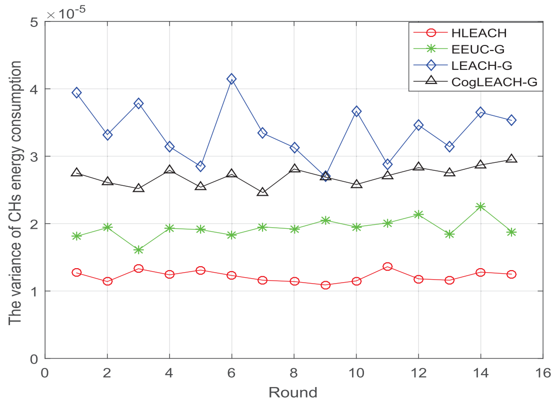

FIGURE 9. The comparison of the balance of the energy consumption among CHs under different algorithms.

among CHs, and EEUC-G, CogLEACH and LEACH-G algorithms rank second, third and fourth, respectively. This is because the proposed algorithm not only considers the distribution of CHs in the multi-hop HCRSN, but also the distribution of CNs among clusters, while EEUC-G only consider the distribution of CHs. Both CogLEACH-G and LEACH-G algorithms don't take into account the two points. Furthermore, the selection of CHs in LEACH-G is more random than that in CogLEACH-G since the latter considers the number of idle channels detected by CNs.

E. THE COMPARISON OF THE NUMBER OF CLUSTERS UNDER DIFFERENT ALGORITHMS

Fig. 10 shows the comparison of the number of clusters under different algorithms before 100 rounds. It can be seen from the figure that the proposed algorithm can provide the most stable number of clusters compared with other algorithms.

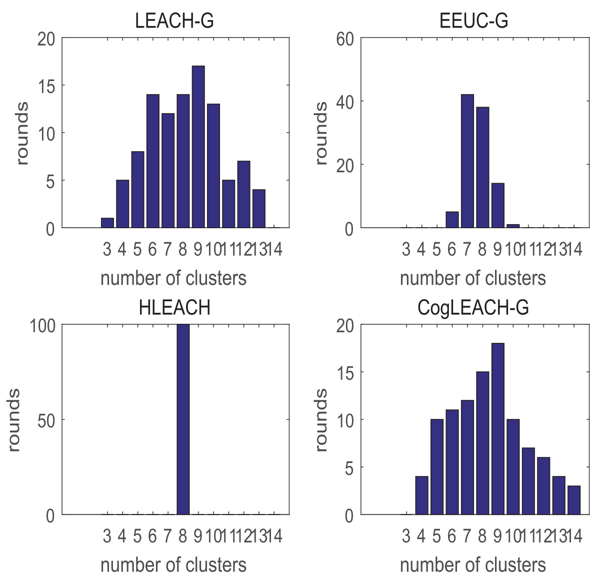

FIGURE 10. The comparison of the number of clusters under different algorithms.

This contributes to guarantee enough high channel detection probability of each cluster in all rounds.

F. THE COMPARISON OF NETWORK LIFETIME

The network lifetime is an important performance indicator of WSN, and it is often represented by the survival time of nodes. In HCRSN, the proportion of numbers and initial energy of two types of nodes can impose significant impact on the network lifetime. We thus show the comparison of the network lifetime under different proportion of numbers and initial energy of two types of nodes (the total energy of nodes in the network is $100J$) in Fig. 11, Fig. 12 and Fig. 13. Different from the existing homogeneous nodes based WSN, there are two completely different types of nodes in HCRSN. Therefore, we show the survival time of the two types of nodes in the comparison of the network lifetime.

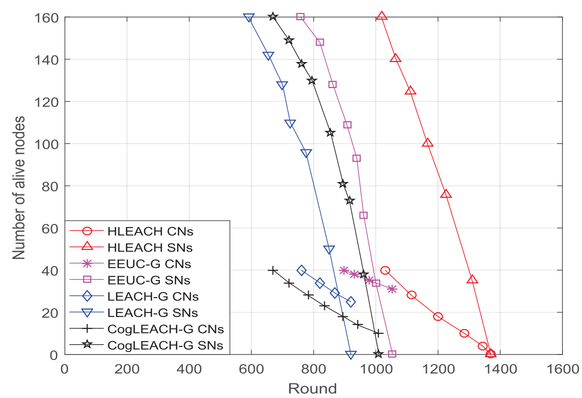

FIGURE 11. The comparison of numbers of alive nodes under different algorithms ($m = 0.2, E_{CN}/E_{SN} = 8.5$).

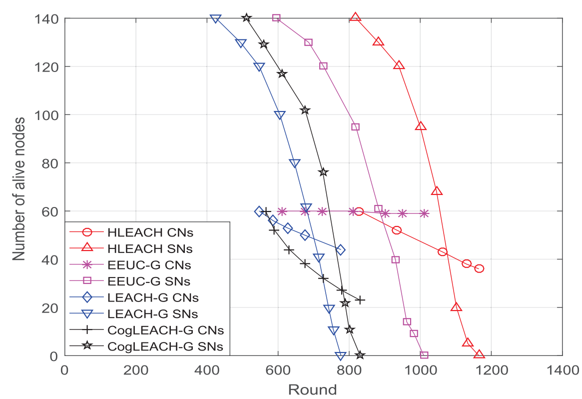

FIGURE 12. The comparison of numbers of alive nodes under different algorithms ($m = 0.3, E_{CN}/E_{SN} = 8.5$).

In the Fig. 11, m is the proportion of CNs in total numbers, and E_{CN}/E_{SN} is the initial energy ratio of CNs to SNs. It can be seen from Fig. 11 that under the condition of $m = 0.2, E_{CN}/E_{SN} = 8.5$, the network lifetime under the proposed algorithm is the longest among the algorithms, and no nodes die before 1018 rounds. In the case, the first and last death nodes of the two types of nodes almost simultaneously occur. This indicates that the proposed algorithm can provide

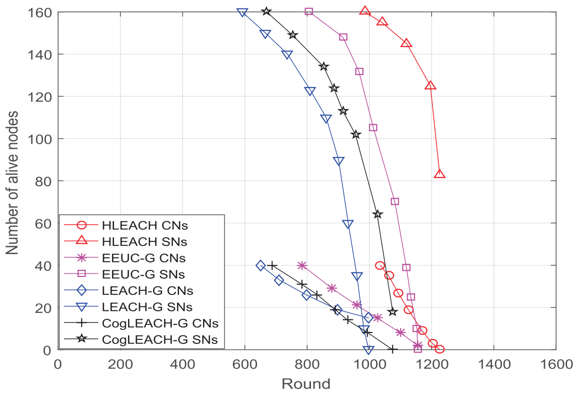

FIGURE 13. The comparison of numbers of alive nodes under different algorithms ($m = 0.2$, $E_{CN}/E_{SN} = 7$).

the best balance of the energy consumption among CNs and SNs in the case.

It can be seen from Fig. 11, Fig. 12 and Fig. 13 that under the condition of $m = 0.2$ and $E_{CN}/E_{SN} = 8.5$, the lifetime of the two types of nodes in the proposed algorithm is equivalent. When the initial energy ratio of CNs to SNs remains unchanged and the number of CNs increases (i.e, under $m = 0.3$, $E_{CN}/E_{SN} = 8.5$, as shown in Fig. 12), the lifetime of the two types of nodes is different. In the case, when all SNs die, some CNs survive due to the increase of the number of CNs. However, under the condition of $m = 0.2$ and $E_{CN}/E_{SN} = 7$ (Fig. 13), many SNs survive when all CNs die since the initial energy of CNs to SNs is reduced.

It can be seen from Fig. 11, Fig. 12 and Fig. 13 that under the condition of $m = 0.2$ and $E_{CN}/E_{SN} = 8.5$, some CNs under EEUC-G, CogLEACH-G and LEACH-G algorithm survive when all SNs die. Under the condition of $m = 0.3$ and $E_{CN}/E_{SN} = 8.5$, more CNs survive when all SNs die since the number of CNs increases. Under the condition of $m = 0.2$ and $E_{CN}/E_{SN} = 7$, the lifetimes of the two types of nodes under EEUC-G algorithm are almost equivalent, some SNs under CogLEACH survive when all CNs die, and less CNs under LEACH-G survive when all SNs die since the initial energy ratio of CNs to SN is reduced.

It can be seen from Fig. 11, Fig. 12 and Fig. 13 that though the network lifetimes under the proposed algorithm in all three cases are different, they are always the longest among the four algorithms. This proves that the proposed algorithm can more efficiently employ energy than other algorithm.

It can be seen from Fig. 11, Fig. 12 and Fig. 13 that under the proposed algorithm, the proportion of numbers and initial energy of CNs and SNs can have significant impact on the balance of the energy consumption between CNs and SNs, and further affect the network lifetime and deployment cost.

Therefore, the optimal deployment proportion of numbers and initial energy of CNs and SNs should be studied to balance the energy consumption between CNs and SNs such that the energy of CNs and SNs can be completely employed (i.e. maximize the energy utilization efficiency).

G. DETERMINATION OF THE PROPORTION OF CNs IN TOTAL NUMBERS

Unlike traditional homogeneous WSN, HCRSN consists of two types of nodes. In the HCRSN, CNs in turn act as CHs, which undertakes many functions such as SS, data fusion, data forwarding and the management and maintenance of the clusters. Therefore, the deployment proportion of CNs in total numbers has great impact on the network performance and it can greatly affect the deployment cost.

According to the formula (16), when the number of CNs is very small (i.e. the proportion of CNs in total numbers of nodes is very low), the number of clusters in the network is very large. This may make the average size of clusters be very small, and further there may be only very few CNs in each cluster. This can lead to very low channel detection probability, which cannot satisfy the communication requirement of the network.

According to the formula (16), when the number of CNs is very large (i.e. the proportion of CNs in total numbers of nodes is very high), the number of clusters in the network is very small. This may make the average size of clusters be very large, and further there may be too many CNs in each cluster. This can lead to the sharp increase of the deployment cost, which contradicts the low-cost deployment requirement of HCRSN.

Therefore, the proportion of CNs in total numbers nodes should be well designed such that each cluster in the network can obtain enough high channel detection probability at the lowest deployment cost.

Fig. 14 shows the average channel detection probability of clusters under different numbers of CNs. It can be seen from Fig. 14 that when the number of CNs is 10 (the deployment proportion is 5%), the average channel detection probability is very low. With the growth of the deployment proportion, the channel detection probability increases. When the number of CNs is 40 (i.e. the deployment proportion is 20%), the channel detection probability reaches 99%. When the number of CNs continues to increase, the increase of the average channel detection probability is very little.

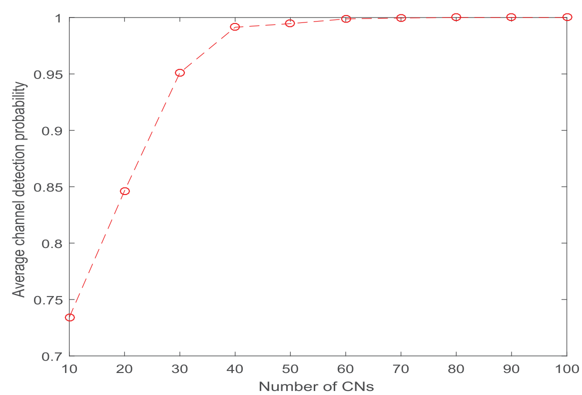

FIGURE 14. Average channel detection probability of clusters under different numbers of CNs.

Fig. 15 shows the average network energy consumption per round under different numbers of CNs. It can be seen from Fig. 15 that the average network energy consumption increases with the growth of the number of CNs. This is because though the increase of the number of CNs participating in CSS can increase the channel detection probability and further decrease the energy consumption caused by data retransmission, it can greatly increase the energy consumption caused by SS.

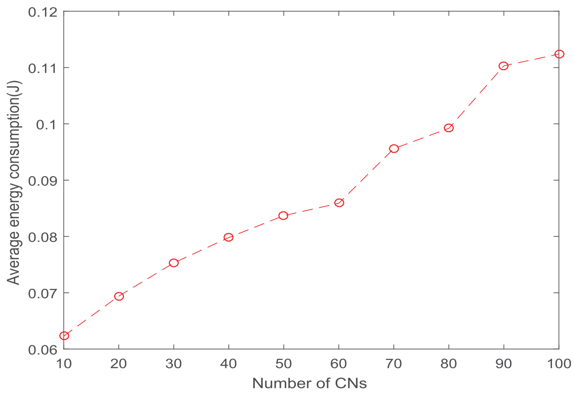

FIGURE 15. **The average network energy consumption per round under different numbers of CNs.**

It can be seen from Fig. 14 and Fig. 15 that less CNs is required to decrease the energy consumption but more CNs is required to increase the channel detection probability. Therefore, there exists a compromise in the number of CNs, and further it can be concluded that the minimum number of CNs that can satisfy the requirement of channel detection probability in HCRSN (e.g. 99%) is the optimal compromise, which lead to the least energy consumption.

Therefore, we have

$$1-(1-p_d)^{\frac{K\cdot m}{q_{opt}}}=0.99 \tag{21}$$

Substituting formula (16) into the above formula, we can obtain the following equation regarding m.

$$\xi\cdot m^5-(L_1-L_2)^2m^2+2L_1\cdot m\cdot(L_1-L_2)-{L_1}^2=0 \tag{22}$$

where $\zeta=(\frac{\ln 0.01}{\ln(1-p_d)})^5(\frac{1}{\frac{3}{2}\pi\sqrt{\pi}\cdot L_1E_{elec}})^2$, $\xi=\frac{K^5}{\zeta\cdot(K\cdot\varepsilon_{fs}\cdot H^2)^2}$.

The equation (22) is a Quintic Equation, which has been proved that there is no analytical solution. However, we can easily solve its numerical solution since $m\in(0,0.5)$.

H. THE DETERMINATION OF THE INITIAL ENERGY RATIO OF CNs to SNs

The initial energy ratio of CNs to SNs can impose great impact on the balance of the energy consumption between CNs and SNs, thus it can not only affect the network lifetime, but also network deployment cost. In order to balance the energy consumption between CNs and SNs (i.e. the energy resource of CNs and SNs can be completely utilized), intuitively, the initial energy settings of CNs and SNs should be proportional to the speed of their own energy consumption (i.e. the energy consumption per round). Based on the proportion of CNs in total numbers m, the theoretic initial energy ratio of CNs to SNs can thus calculated as follows.

$$\begin{aligned}R_{theo}^{ini}&=\frac{\overline{S_C}}{\overline{S_S}}\\&=\frac{(q\cdot E_{CH}+(K\cdot m-q)\cdot E_{non-CH\,CN})\,/\,(K\cdot m)}{E_{SN}}\end{aligned} \tag{23}$$

Note that the formula (23) is based on the case without dead nodes. When CNs start to die, the total energy consumption of CNs is always less than before due to the decrease of energy consumption caused by SS, and further the average speed of the energy consumption of CNs is always lower than before, as can be seen from Fig. 16. In Fig. 16, CNs start to die in the 330th round, the speed of their energy consumption starts to decrease. Therefore, the calculation value of the formula (23) is always higher than the actual value.

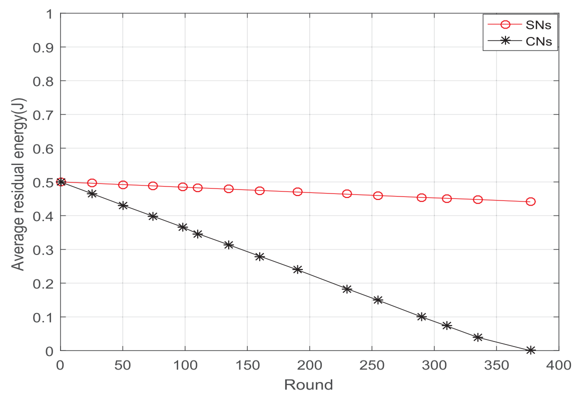

FIGURE 16. **Average residual energy of CNs and SNs under $m = 0.2$ and the same initial energy.**

Fig. 16 shows the average residual energy of CNs and SNs under $m = 0.2$ and the same initial energy.

It can be seen from Fig. 16 that when the energy of CNs has been exhausted, the average residual energy of SNs is 0.4411 J. The actual initial energy ratio of CNs to SNs can thus be calculated as follows.

$$R_{actu}^{ini}=\frac{0.5}{0.5-0.4411}=8.5<R_{theo}^{ini}=\frac{\overline{E_{CN}}}{\overline{E_{SN}}}=9 \tag{24}$$

Therefore, the calculation value of the formula (23) can considered as the reference value. In reality, the initial energy ratio of CNs to SNs can be designed to equal the calculation value of the formula (23) or the lower value than it.

I. MESSAGE COMPLEXITY

The clustering algorithm is message-driven, thus the message complexity of the proposed algorithm is calculated and compared with those of other algorithms, as shown in table 2. It can be seen from table 2 that the message complexity of all the algorithms per round is $\mathcal{O}(K)$. The complexity under our

TABLE 2. Parameter setting.

Parameter	Setting
Simulation area	$200m * 200m$
Total number of nodes	200
Number of PUs	5
Number of available channels	5
Initial energy of the nodes	$0.5J$
E_{sense}	$58.9mW$
E_{elec}	$50nJ/bit$
E_{DA}	$5nJ/bit$
ε_{fs}	$10pJ/bit/m^2$
ε_{mp}	$0.0013pJ/bit/m^4$
p_d	0.7
d_0	$87m$
The size of the data sensed by SNs L_1	$2000bit$
The size of the detected result by CNs L_2	$80bit$
Packet size of intra-cluster data fusion	$2000bit$
Packet size of control information	$80bit$

TABLE 3. Message complexity.

Algorithm	Message complexity	$K = 200, m = 0.2$
HLEACH	$K(2m + 1) + 1$	281
EEUC-G	$K(2m + 1)$	280
CogLEACH-G	$K(m + 1) + 1$	241
LEACH-G	K	200

proposed algorithm is a little higher than other algorithms. However, the performance is the best, as mentioned in the previous text.

J. SIMULATION SNAPSHOTS OF THE PROPOSED CLUSTERING ALGORITHM

Fig. 17 shows a simulation snapshot where there are not dead nodes, and Fig. 18 shows the simulation snapshot of the 1280th round where there are many dead nodes. It can be observed from Fig. 18 that when the clustering algorithm is executed in the 1280th round, the number of clusters in the network is decrease to 6 and the dead CNs and SNs are almost evenly distributed in the HCRSN.

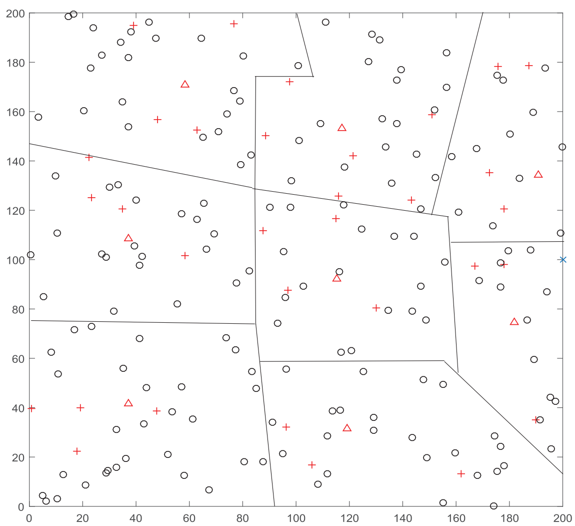

FIGURE 17. Simulation snapshot without dead nodes ('o' denotes a SN, '+' is a CN, 'x' is the sink node, and '△' is a CH).

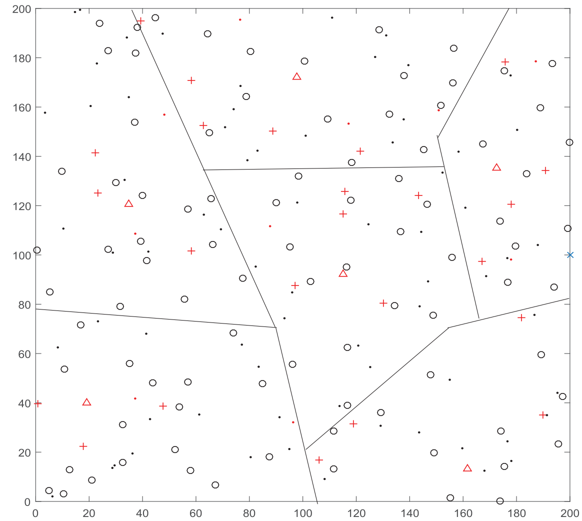

FIGURE 18. The simulation snapshot of the 1280th round (the black point denotes dead SNs, and the red point denotes dead CNs).

V. CONCLUSION AND FUTURE WORK

In this paper, we proposed a HLEACH algorithm for multi-hop HCRSN. In the algorithm, the sink node first updates and broadcasts the global information, and then each CN calculates itself competition radius after receiving the broadcast information based on the deployment density of CNs, followed by the competition for CHs based on the proposed competition rules. In order to enable CHs to more evenly distribute in the HCRSN, some redundant CHs are deleted targeting the optimal number of clusters in the CHs' censoring stage. To energy-efficiently balance the distribution of CNs among clusters and the energy consumption among CHs, the non-CH CNs and SNs select the nearby CHs with the minimum value to join based on the calculation formulas of weights summation of several factors such as the distance and connection degree. Experimental results show that the proposed algorithm has the best performance in terms of channel detection probability, network lifetime and the balance of the distribution of CNs among clusters and the energy consumption among CHs. Finally, the optimal deployment proportion of numbers and the initial energy of CNs and SNs are theoretically derived to maximize the energy utilization efficiency, i.e. the ratio of the network lifetime to the deployment cost. In future work, we plan to further study the deployment proportion of numbers and the initial energy of CNs and SNs, which is of significance for the actual deployment of HCRSN. Furthermore, we also plan to study the spectrum sensing algorithm in the HCRSN to reduce energy consumption and deployment cost. The research issues for potential researchers include but not limit to the message-interaction protocol between CNs and SNs, the MAC protocol for HCRSN and energy-efficient cooperative SS for different application scenarios.

APPENDIX
THE EQUATION (15) IS A CONCAVE FUNCTION WITH RESPECT TO q

Substituting equation (7) into equation (15), we can get

$$E_{round} = q\,(E_{CH} + A + B) \tag{25}$$

where

$$\begin{aligned}
A &= (\frac{K \cdot m}{q} - 1)E_{non-CH\,CN} \\
B &= \frac{K(1-m)}{q} \cdot E_{SN} \\
E_{round} &= q \cdot E_{CH} + K \cdot m \cdot E_{non-CH\,CN} \\
&\quad - q \cdot E_{non-CH\,CN} + K(1-m) \cdot E_{SN}
\end{aligned} \tag{26}$$

Substituting equations (4-14) into the equation (26), we can get

$$E_{round} = q \cdot C + q \cdot D + K(1-m) \cdot E + K \cdot m \cdot F - q \cdot G \tag{27}$$

where

$$\begin{aligned}
C &= \frac{K(1-m)}{q} \cdot L_1 \cdot E_{elec} + (\frac{K \cdot m}{q} - 1) \cdot L_2 \cdot E_{elec} \\
&\quad + \frac{K(1-m)}{q} \cdot L_1 \cdot E_{DA} + L_3 \cdot E_{elec} + L_3 \cdot \varepsilon_{fs} \cdot \frac{4H^2}{\pi q} \\
&\quad + E_{sense} + E_{elec} \cdot L_4 \\
D &= L_2 \cdot E_{elec} + L_2 \cdot \varepsilon_{fs} \cdot \frac{H^2}{2\pi q} \\
E &= L_1 \cdot E_{elec} + L_1 \cdot \varepsilon_{fs} \cdot \frac{H^2}{2\pi q} + E_{elec} \cdot L_2 \\
F &= L_2 \cdot E_{elec} + L_2 \cdot \varepsilon_{fs} \cdot \frac{H^2}{2\pi q} + E_{sense} \\
G &= L_2 \cdot E_{elec} + L_2 \cdot \varepsilon_{fs} \cdot \frac{H^2}{2\pi q} + E_{sense}
\end{aligned} \tag{28}$$

Rewriting the above equation can get

$$\begin{aligned}
E_{round} &= 2K(1-m) \cdot L_1 \cdot E_{elec} + K \cdot m \cdot L_2 \cdot E_{elec} \\
&\quad - q \cdot L_2 \cdot E_{elec} + K(1-m) \cdot L_1 \cdot E_{DA} \\
&\quad + q(\frac{\sqrt{\pi q}}{4} + \frac{1}{2}) \cdot L_1 \cdot E_{elec} \\
&\quad + (\frac{\sqrt{\pi q}}{4} + \frac{1}{2}) \cdot \varepsilon_{fs} \cdot \frac{4H^2}{\pi} \\
&\quad + q(\frac{\sqrt{\pi q}}{4} - \frac{1}{2}) \cdot L_1 \cdot E_{elec} \\
&\quad + K(1-m) \cdot L_1 \cdot \varepsilon_{fs} \cdot \frac{H^2}{2\pi q} + K \cdot m \cdot L_2 \cdot E_{elec} \\
&\quad + K(1-m) \cdot L_2 \cdot E_{elec} + K \cdot m \cdot E_{sense} \\
&\quad + K \cdot m \cdot L_2 \cdot \varepsilon_{fs} \cdot \frac{H^2}{2\pi q}
\end{aligned} \tag{29}$$

Taking the partial derivative of the equation (29) with respective to q can get

$$\begin{aligned}
E'_{round} &= \frac{3\sqrt{\pi}}{4} \cdot L_1 \cdot E_{elec} \cdot \sqrt{q} - L_2 \cdot E_{elec} \\
&\quad + \frac{H^2}{2\sqrt{\pi}} \cdot \varepsilon_{fs} \cdot \frac{1}{\sqrt{q}} \\
&\quad + K \cdot m \cdot L_2 \cdot \varepsilon_{fs} \cdot \frac{H^2}{2\pi} \cdot \left(-\frac{1}{q^2}\right) \\
&\quad + K(1-m) \cdot L_1 \cdot \varepsilon_{fs} \cdot \frac{H^2}{2\pi} \cdot \left(-\frac{1}{q^2}\right)
\end{aligned} \tag{30}$$

Its second-order partial derivative with respect to q can be written as:

$$\begin{aligned}
E''_{round} &= \frac{3\sqrt{\pi}}{8} \cdot L_1 \cdot E_{elec} \cdot \frac{1}{\sqrt{q}} - \frac{H^2\varepsilon_{fs}}{4\sqrt{\pi}\cdot} \cdot \frac{1}{q\sqrt{q}} \\
&\quad + \frac{H^2\varepsilon_{fs}(K \cdot m \cdot L_2 + K(1-m) \cdot L_1)}{2\pi} \frac{2}{q^3}
\end{aligned} \tag{31}$$

Let γ denote the ratio of the latter two items in formula (31), we can get

$$\begin{aligned}
\gamma &= \frac{4}{\sqrt{\pi}} \frac{K\,(mL_2 + (1-m)L_1)}{q^{\frac{3}{2}}} \\
&\overset{\frac{4}{\sqrt{\pi}}>1}{>} \frac{K\,(mL_2 + (1-m)L_1)}{q^{\frac{3}{2}}} \\
&\overset{L_1>L_2}{>} \frac{KL_2}{q^{\frac{3}{2}}} \xrightarrow{Let\ \ K=nq} \frac{nL_2}{q^{\frac{1}{2}}} = \frac{(nL_2)^2}{q} \gg 1
\end{aligned} \tag{32}$$

where $m \in (0, 1)$, $q > 1$, $n > 1$.

Therefore, we can get

$$-\frac{H^2\varepsilon_{fs}}{4\sqrt{\pi}\cdot} \cdot \frac{1}{q\sqrt{q}} + \frac{H^2\varepsilon_{fs}(K \cdot m \cdot L_2 + K(1-m) \cdot L_1)}{2\pi} \frac{2}{q^3} > 0 \tag{33}$$

Furthermore, we can obtain $E_{round}{}'' > 0$, which can prove that the function $E_{round}(q)$ is a concave function. That is to say, the function $E_{round}(q)$ has the minimum value.

Let E'_{round}=0, we get

$$\begin{aligned}
E'_{round}(q) &= \frac{3\sqrt{\pi}L_1E_{elec}}{4}\sqrt{q} + \frac{H^2\varepsilon_{fs}}{2\sqrt{\pi}} \frac{1}{\sqrt{q}} \\
&\quad - \frac{KH^2\varepsilon_{fs}}{2\pi}(m \cdot L_2 \cdot +(1-m) \cdot L_1) \frac{1}{q^2} \\
&\quad - L_2 \cdot E_{elec} = 0
\end{aligned} \tag{34}$$

Let $z = \sqrt{q}$, then

$$\begin{aligned}
E'_{round}(z) &= az^5 - bz^4 + cz^3 - d \\
&= az^5 + (-bz + c)z - d = 0
\end{aligned} \tag{35}$$

where

$$\begin{aligned}
a &= \frac{3\sqrt{\pi}L_1E_{elec}}{4} \\
b &= L_2 \cdot E_{elec} \\
c &= \frac{H^2\varepsilon_{fs}}{2\sqrt{\pi}} \\
d &= \frac{KH^2\varepsilon_{fs}}{2\pi}(m \cdot L_2 \cdot +(1-m) \cdot L_1)
\end{aligned} \tag{36}$$

The formula (35) is a Quintic Equation, which has been proved that there is no analytical solution. In reality, it is not hard to understand that $L_1 \gg L_2, E_{elec} \gg \varepsilon_{fs}$, $H \in [100, 10000]$, $K > 100$, we can thus obtain

$$\begin{aligned} &d \gg a, b, c \\ &a \gg b, c \quad or\ a \gg (-bz + c) \end{aligned} \tag{37}$$

Therefore, $E'_{round}(z)$ is mainly dominated by the term $az^5 - d$, and further the term $-bz^4 + cz^3$ in (35) can be ignored. The solution to equation (31) can thus be solved, which can be represented as follows.

$$q_{opt} = \left\lfloor \left(\frac{2H^2 K \varepsilon_{fs} \left((1-m) L_1 + m L_2 \right)}{3\pi^{\frac{3}{2}} L_1 E_{elec}} \right)^{\frac{2}{5}} + 0.5 \right\rfloor \tag{38}$$

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