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Energy-Efficient Cluster Head Selection Scheme Based on Multiple Criteria Decision Making for Wireless Sensor Networks

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Abstract Energy efficiency is an essential issue in the applications of wireless sensor networks (WSNs) all along. Clustering with data aggregation is a significant direction to improve energy efficiency through software. The selection of cluster head (CH) is the key issue in the clustering algorithm, which is also a multiple criteria decision making (MCDM) procedure. In this paper, a novel fuzzy multiple criteria decision making approach, which is based on trapezoidal fuzzy AHP and hierarchical fuzzy integral (FAHP), is introduced to optimize the selection of cluster heads to develop a distributed energy-efficient clustering algorithm. Energy status, QoS impact and location are taken into account simultaneously as the main factors that can influence the selection of cluster heads while each factor contains some sub-criteria. Fuzzy multiple attribute decision making is adopted to select optimal cluster heads by taking all factors into account synthetically. According to these criteria, each node computes a composite value by using fuzzy Integral. Then this composite value is mapped onto the time axis, and a time-trigger mechanism makes the node broadcast cluster head information. The rule that "first declaration wins" is adopted to form the cluster. Simulation results denote that our proposed scheme has longer lifetime and more eximious expansibility than other algorithms.

Keywords Wireless sensor networks · Clustering · Multiple criteria decision making · Trapezoidal fuzzy AHP · Hierarchical fuzzy integral

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1 Introduction

The recent advances in micro-sensor and wireless communication technology make a minute node a viable gadget to deploy a low power, inexpensive sensor in large scale [1]. These sensor nodes are usually battery-driven. In some scenario the sensor nodes may be deployed in unattended regions, so that the nodes cannot replenish the energy depleted. The nodes that lost energy may cause the disconnection of the entire network. Therefore, optimizing the usage of the limited energy and extending the lifetime of wireless sensor networks has been the focus of current research. This need to design novel energy-efficient solutions for routing and self-organization, so as to prolong the network lifetime.

Clustering is one of the basic approaches for designing energy-efficient, robust and highly scalable distributed sensor networks [2]. It consists in obtaining a hierarchical organization of the network. This domain has been intensively studied because it is very useful when you want to achieve an energy-efficient message transmission through the network. The cost of sending a message is higher than computation and hence it is advantageous to organize the sensors into clusters [3,4], where the data gathered by the sensors is communicated to the base station (BS) through a hierarchy of cluster heads (CHs). This means that creation of clusters and assigning special tasks to CHs can greatly contribute to overall system scalability, lifetime, and energy efficiency [5]. Therefore, many cluster-based algorithms have been widely studied and used. Selection of CHs, which is a pivotal step in cluster-based algorithm, can seriously influence the performance of the clustering algorithm. Under normal circumstances, whether a node can be a CH or not depends not only on its energy level, but also on other factors such as energy consumption, channel lost and neighbor density, etc. In this sense, the selection of CH can be regarded as a multiple criteria decision making issue. According to this perspective, we propose an energy-efficient CH selection scheme based on multiple criteria decision making for wireless sensor networks, to improve the performance of the entire network. A novel multiple attribute decision making based on trapezoidal fuzzy AHP and hierarchical fuzzy integral (FAHP) is described in detail about how to select CHs distributed in this paper. Through simulation contrasted with previous works, we show that our approach can outperform in energy efficiency and expansibility.

The rest of the paper is organized as follows. We review the related works in Section 2. Section 3 introduces the related models. Our proposed scheme FAHP is described in detail in Section 4. The simulation result and related analysis will be illustrated in Section 5. Finally, in Section 6, we draw the conclusion.

2 Related Works

There has been very few directed research relating to decision making in sensor networks. The existing clustering algorithms differ on the criteria for the selection of the CHs. According to the current research findings, the previous work about the selection method of the CHs can be summarized as follows.

LEACH (Low-Energy Adaptive Clustering Hierarchy) [4] and DCHS (deterministic cluster-head selection) [6] apply randomized rotation of the CHs to distribute the energy load among the sensor nodes evenly in the entire network. The CHs selection of them uses a probability scheme that each node determines whether it is able to be the CH only based on the random number it generated. Although the complexity of LEACH is low, the lack of energy consideration and the irregular distribution of the CHs make the algorithm energy-inefficient.

Unlike LEACH, DCHS introduces residual energy in the probability threshold, which is able to improve the energy efficiency to a certain extent.

HEED (Hybrid Energy-Efficient Distributed clustering) [7] is a distributed clustering scheme in which CH nodes are picked from the deployed sensors based on a certain probability which is related to a hybrid of energy and communication cost. HEED does not select CHs randomly. Only sensor nodes that remain high residual energy and lower intra-communication costs can become CHs. Once selected, the CH is kept for a fixed number of iterations. All the non-CH nodes select the corresponding CH in terms of the lowest intra-cluster communication cost. Clusters generated by HEED are more well-balanced than LEACH. CHs keep a fixed number of iterations is also different from LEACH, which reduce the unnecessary huge setup overhead associated with the CH selection process. Although HEED creates distributed clusters without the size and the density of the sensor network being known, yet the cluster topology fails to achieve minimum energy consumption in intra-cluster communication [8]. Because sensors that are not covered by any CH double their probability of becoming a CH until all sensors are covered by at least one head, HEED cannot guarantee the optimal number of elected CHs. Furthermore, only node's residual energy is used as the primary parameter during the process of CH election, whereas other factors that are able to influence energy efficiency cannot be taken into consideration, especially network connectivity.

T-ANT [9] confirms the optimal CH's quantity firstly, then the BS releases the optimal number of ants (agents) in the first round. These ants are not simultaneously released, after the BS has released an ant to one of its neighbors at random and waited for a period of stochastic time, the next ant could be released. T-ANT implements this operation repeatedly until all ants are released. The node that has received the ant continues transmitting the ant to a stochastic neighboring node, until TTL's (time-to-live) value reaches zero. If TTL expires, the node which is possessing an ant becomes the CH, and the corresponding CH advertisement is broadcasted. The pheromone is not generated in the ant release's process. The link between the member node and the corresponding CH is lay a certain amount pheromone according to the residual energy of the node and the CH's number in the node's radio range. A regular node chooses the nearest CH to join by sending a JOIN message with its pheromone level. At the beginning of next round, CH transmits ant to the new CH, which is the neighbor node that has the highest pheromone level. Simulation results demonstrate that T-ANT achieves even distribution of CHs and even distribution of members among the clusters, which results in the better network lifetime compared to the competitor protocols. It is also found that T-ANT is able to maintain substantially lesser state overhead in memory. However, T-ANT depends on random propagation to select CHs in the first round, during which the residual energy and the location of the CH cannot be guaranteed. This defect will impact on the CH selection of the next several rounds. Moreover, the pheromone function is only based on the residual energy and the number of CHs, in which the number of the member nodes and the distance between each CH-member pair are not taken into account at all.

Many fuzzy logic control algorithms are widely used in the CH selection. The basic elements of fuzzy logic control are fuzzifier, inference engine, Fuzzy Rule Base (FRB) and defuzzifier, as shown in Fig. 1.

Gupta [10] believes that the overhead of CH election may be highly reduced by using fuzzy logic. Mamdani Method is used as the fuzzy inference technique, as well as the COG (Center of Gravity) is adopted as defuzzifier approach. Three fuzzy variables—energy, concentration and centrality are used to optimize CH selection in order to extend the network lifetime efficiently. The operation of this fuzzy CH election scheme is divided into rounds each consisting of a setup and steady state phase. During the setup phase, the BS collects the energy and location information from all sensor nodes and elects the CHs using fuzzy if-then rule

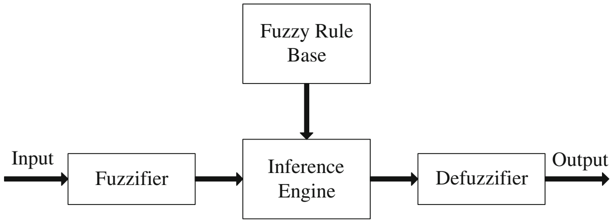

Fig. 1 Fuzzy logic controller structure

according to the collected fuzzy variables and then the cluster is organized. In the steady state phase, the CHs collect the sensed data and perform data fusion functions to compress the data into a single signal, then transmit the composite signal to the BS directly. Though this clustering mechanism prolongs the network lifetime, some demerits caused by the centralized algorithm exist even so. The BS has to collect information from all sensor nodes, which may be very complex and can generate more overhead. Furthermore, the centralized algorithm is only suitable for small or medium sized network.

As the distributed version of the clustering algorithm mentioned above, CHEF [11] uses two fuzzy variables—energy and local distance to compute a chance. Unlike its centralized version, each node computes the chance of its own independently in CHEF, which enhance the expansibility of the network. Mamdani Method and COG are both applied in calculating chance. CHEF limits the number of the candidate CHs based on the equation $P_{o\,pt} = \alpha \times P$, where P is the ratio of the preferred number of CHs similar to LEACH and α is a constant value that defines the ratio of the candidate for CH. Once a node becomes a candidate, it broadcasts its chance to the vicinity. After the node has received all chances, if the chance of itself is bigger than that of the other nodes, the sensor node elected itself as the CH and advertises a CH message. Each non-CH node receives the CH messages and selects the closest CH as its CH and sends a Join message to the CH. CHEF makes the CHs distribute over the network evenly, therefore the longevity of the network is achieved.

The clustering scheme proposed in [12,13] is similar to CHEF. Three variables—distance of cluster centroid, remaining battery power of sensor and network traffic are selected to be the inputs of the fuzzy logic controller. The output linguistic parameter is the probability of CH selection. Likewise, Mamdani Method and COG are used too. Simulation results demonstrate that this algorithm makes a good selection of the CHs.

FSCA [14] is, in fact, an improved version of ACE [15]. In FSCA, each node is embedded with two fuzzy modules: the Initiation Fuzzy Module (IFM) and Migration Fuzzy Module (MFM). The IFM has two inputs—the node lifetime since the protocol starts and the node's total number of Loyal Followers. Based on IFM, the node determines whether to be a CH or not in the initialization phase. During the migration process, the cluster migrates around the node which has the highest chance of being a CH. The chance of being a CH is determined by the MFM. The MFM takes the node's Loyal Followers and the reserved power as inputs. The output is the chance of being the new CH. The other steps in FSCA are the same as ACE. Simulations show that FSCA distributes clusters uniformly over the sensor network as well as ACE and with an advantage over ACE that it extends the network lifetime.

EESH [16] (energy efficient strong head) is proposed to improve the performance for prolonging the network lifetime. EESH distinguishes the strong or the weak nodes through the BS firstly. Then each node calculates the cost of its own. The cost is determined by four factors—the energy of the node, the residual energy of neighbors, the distances from the neighbors and the amount of the nodes nearby. Simulation results show that EESH is able to prolong the lifetime of wireless sensor networks, as well as slower the trend of network usage dropping especially at early stages before and after some nodes begin to die. EESH announces that the energy of the node is the most important one among the four factors, but this idea is not reflected in the Cost formula. From the Cost formula, the four factors are equally important. In addition, the centralized mode is adopted in EESH, which cannot be suitable for large-scale sensor networks.

MWBC [17] is a multi-weight based clustering algorithm for maximal-lifetime wireless sensor network design, which takes into consideration many factors such as the ideal degree, current energy, transmission power, link quality, and relatively position of nodes. First of all, nodes obtain the parameters that can describe the situation of the local network through exchanging information each other. Then these parameters are dynamically calculated to be the weight, which the node holds to compete for CH, through the weighted average approach. Simulation results show that MEBC algorithm can obtain more reasonable cluster distribution and better load balancing features. However, the weight of each parameter is determined according to trial and error approach, which results in the lack of theoretical support and will influence the performance of the whole algorithm. Moreover, linear weighted calculation has its limitations, and it cannot truly reflect the relationship between the various network parameters.

The clustering scheme proposed in [18] uses probability to select CHs. In every round, each node decides whether it will be a CH in that round based on the threshold T. This threshold is set in terms of the residual energy and the number of alive neighbor nodes by using the weighted average method. If a randomly generated number between 0 and 1 is smaller than T, the node elects itself as a CH. Simulation identifies that this approach extends the lifetime of the sensor network for about 50% compared to the existing schemes randomly selecting the CHs. Similar to MWBC, the weights of the two factors are determined according to experience, which is in defect of theoretical basis.

AHP (Analytical Hierarchy Process) [19] is a centralized CH selection scheme, which uses MCDM approach to select appropriate CHs. Residual energy, mobility and the distance to the involved cluster centroid are regarded as three criteria contributing to the network lifetime. The BS collects all nodes' correlative information and makes the decision based on the AHP MCDM approach. The trigger conditions of CH re-selection are adaptive based on the mobility and the remaining energy of the nodes. The simulation results demonstrate that AHP approach can improve the network lifetime remarkably, especially for differentiated initial energy of nodes. Nevertheless, the centralized approach limits the size of the network.

Decision Trees (DTs) [20], which is used in Decision Support Systems, are introduced into the CH selection process. This scheme is based on four factors such as the distance of a node from the cluster centroid, the remaining battery power, the degree of mobility, and the vulnerability index. In each round, the BS runs the DTs algorithm and selects the nodes suitable for being CHs after collecting the information from all nodes in the network. The experiments results not only illustrate that DTs algorithm could result in long lifetime clusters than others with any density of sensor networks, but also show that the well-distributed clusters are achieved. Similar to AHP scheme, DTs only suits small-size network with no expansibility requirement.

A fundamental observation is that any CH election mechanism that is based on a concrete metric, e.g. the residual energy level, the number of neighbors, the cost, can be manipulated in principle. Though in most solutions the CHs are determine based on a synthetic value, yet different composite operators are introduced in MCDM process. However, it is assumed that the criteria (attributes or objectives) are independent and uncorrelated in the solutions mentioned above. In the real world, most criteria have inter-dependent or interactive characteristics, so that they cannot be evaluated by conventional additive measures. Thus the optimal resource cannot be configured, which also makes the performance of the entire network affected.

In order to improve the network performance as much as possible, especially in energy efficiency, we propose a new MCDM CH selection scheme based on trapezoidal fuzzy AHP and hierarchical fuzzy integral in this paper. Three aspects and six attributes, which are likely to directly influence the network lifetime, are taken into account. The three aspects are energy status, QoS impact and node location. Each aspect includes two attributes, which are {residual energy, communication cost between a node and its neighbors}, {link quality, restart number} and {number of neighbors, node marginality}, respectively. Every node performs the proposed selection approach in a distributed fashion. The simulation results exhibit the MCDM CH selection scheme based on trapezoidal fuzzy AHP and hierarchical fuzzy integral can effectively prolong the network lifetime.

3 System Model

3.1 Network Model

We consider a model which is well suited for these sensor networks. It is based on the similar models used in [4,21].

(1) All sensor nodes cannot move after being deployed, and each node has a unique ID.
(2) There is only one BS which lies outside the network.
(3) All sensor nodes are homogeneous. All nodes are synchronized in time.
(4) Each node has the ability to aggregate data; as a result several data packets can be compressed as one packet.
(5) All the nodes are energy constrained with a uniform initial energy allocation. Each node has a fixed number of transmission power levels and power control capability to vary their transmission power.
(6) The BS has a constant power supply and so, has no energy constraints.
(7) Nodes are location-aware, i.e. equipped with GPS-capable antennae. Sensor nodes are aware of base station location.
(8) The bidirectional channel is defined throughout the entire network.

3.2 Wireless Channel Model

The same wireless channel model is put to use in LEACH [3] and this paper, which is composed of the free space model and the multipath fading model. The following equations present the calculation of transmission and receiving energy consumption for a k-bit packet over distance d.

$$E_t(k,d) = \begin{cases} kE_{elec} + k\varepsilon_{fs}d^2 & d < d_0 \\ kE_{elec} + k\varepsilon_{mp}d^4 & d \geqslant d_0 \end{cases} \tag{1}$$

$$E_r(k) = kE_{elec} \tag{2}$$

In the equations, E_{elec} represents the energy consumption in the transmitter or receiver circuitry. ε_{fs} and ε_{mp} indicate the energy dissipation of the transmitter amplifier in the free space model and the multipath fading model, respectively. If a node spends energy E_{fusion} to aggregate one bit, then the energy used in aggregating m data packets to a single packet is:

$$E_f(m,k) = mkE_{fusion} \tag{3}$$

3.3 The Hierarchical Fuzzy Integral Model

On account of some inherent interdependence or interactivity among the criteria, the non-interactive or independent assumption is not realistic in WSNs. Since the fuzzy integral model does not need to assume independency of one criterion from another, it can be used in non-linear situations [22]. Therefore, the hierarchical fuzzy integral is introduced here to analyze and solve the interactive and interdependent criteria issue.

3.3.1 λ-Fuzzy Measure

Let $X = \{x_1, x_2, \ldots, x_n\}$ be the finite set of criteria, and let $P(X)$ denote the power set of X or set of all subsets of X.

Definition 1 A fuzzy measure on the set X of criteria is a set function $g : P(X) \in [0, 1]$ satisfying the following axioms.

$$\begin{array}{ll} (1) & g(\phi) = 0,\ \ g(X) = 1.\ \text{(boundary conditions)} \\ (2) & \text{If } A, B \subset P(X) \text{ and } A \subset B,\ \text{ then } g(A) \leqslant g(B).\ \text{(monotonicity)} \end{array} \tag{4}$$

Let g_λ be a λ-fuzzy measure, and a special kind of fuzzy measure defined on $P(X)$ of a finite set X and satisfying the finite λ-rule. Sugeno [23] introduced the so-called λ fuzzy measure satisfying the following additional property:

$$\begin{aligned} &\forall A, B \in P(X), \quad A \cap B = \phi, \\ &g_\lambda(A \cup B) = g_\lambda(A) + g_\lambda(B) + \lambda g_\lambda(A) g_\lambda(B), \quad \lambda \in (-1, \infty) \end{aligned} \tag{5}$$

According to the definition of g_λ, the finite set $\{x_1, x_2, \ldots, x_n\}$ mapping to function g_λ can be written using fuzzy density $g_i = g_\lambda(\{x_i\})$ as:

$$\begin{aligned} g_\lambda(\{x_1, x_2, \ldots, x_n\}) &= \sum_{i=1}^{n} g_i + \lambda \sum_{i_1=1}^{n-1} \sum_{i_2=i_1+1}^{n} g_{i1} g_{i2} + \cdots + \lambda^{n-1} g_1 g_2 \cdots g_n \\ &= \frac{1}{\lambda} \left| \prod_{i=1}^{n} (1 + \lambda g_i) - 1 \right|, \quad \text{where } \lambda \in (-1, \infty) \end{aligned} \tag{6}$$

From boundary condition $g_\lambda(X) = 1$, the λ value of λ-fuzzy measure g_λ can be calculated by solving

$$1 + \lambda = \prod_{i=1}^{n} (1 + \lambda g_i) \tag{7}$$

3.3.2 Fuzzy Integral

Definition 2 (*Fuzzy integral*) Let g be a fuzzy measure on X and h be a measurable function from X to [0,1]. Assuming that $h(x_1) \geqslant h(x_2) \geqslant \cdots \geqslant h(x_n)$, we can construct Sugeno fuzzy integral as follows:

$$e(h) = \int_X h \mathrm{d}g = \max_{i=1}^{n} \min(h(x_i), g_\lambda(H_i)), \tag{8}$$

where $H_1 = \{x_1\}, H_2 = \{x_1, x_2\}, \ldots, H_n = \{x_1, x_2, \ldots, x_n\}$.

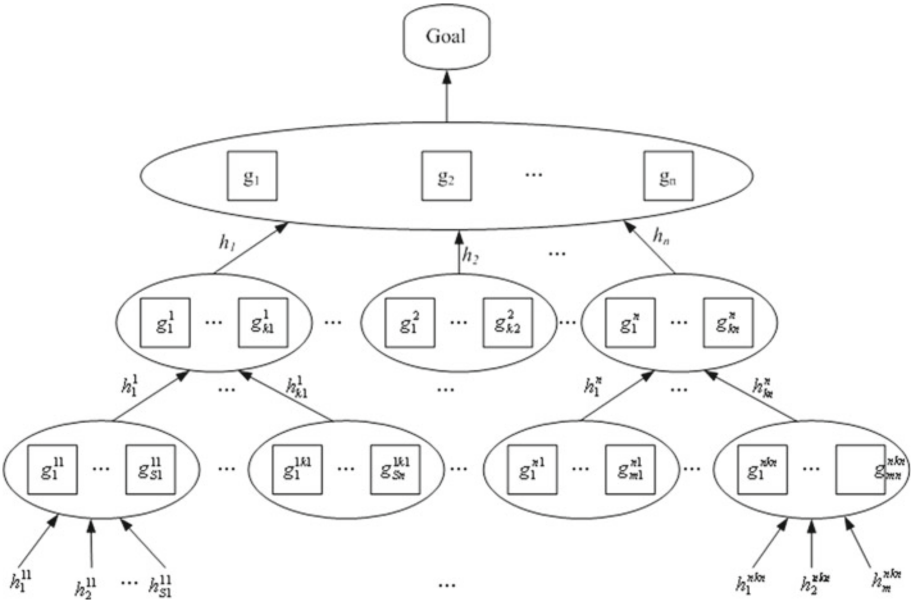

Fig. 2 The hierarchical fuzzy integral model structure

In practice, h can be regarded as the performance of a particular attribute for the alternatives while g stands for the grade of subjective importance (weight) of each attribute. A fuzzy integral of h with respect to g gives the overall evaluation for each alternative [22,24,25].

3.3.3 The Hierarchical Fuzzy Integral Model

The hierarchical fuzzy integral model is constructed based on AHP structure, as shown in Fig. 2. If each circle represents an attribute, then the upper-levels objects' evaluation values can be computed through the evaluation values and the grades of importance on the lower-level objects calculated on integrals Eq. (8). From Fig. 2, $h_1^{11}, h_2^{11}, \ldots, h_{s1}^{11}$ are the evaluation values of the bottom-levels objects while $g_1^{11}, g_2^{11}, \ldots, g_{s1}^{11}$ are the grades of importance. The result h_1^1 is attained by using integrals Eq. (8) to compute the subtotal evaluation values of the first attribute on Level 4. The other subtotal evaluation values can be calculated in the same way. Then all results are $(h_1^1, h_2^1, \ldots, h_{k1}^1), \ldots, (h_1^n, h_2^n, \ldots, h_{kn}^n)$ respectively. Likewise, there are n attributes on Level 3. Here $h_1^1, h_2^1, \ldots, h_{k1}^1$ are the evaluation values, $g_1^1, g_2^1, \ldots, g_{k1}^1$ are the grades of importance, and the result is h_1. The other subtotal evaluation values are $h_2, \ldots, h_n$. Finally, there is only one attribute on Level 2. Here $h_1, h_2, \ldots, h_n$ are the evaluation values and $g_1, g_2, \ldots, g_n$ are the grades of importance. By using Eq. (8) to compute the overall evaluation value, we get the final result on Level 1 [22,24].

4 CH Selection Scheme Based on Multiple Criteria Decision Making

Like the classical clustering algorithms, FAHP is also divided into rounds. Each round is composed of a setup phase and a data transmission phase. Setup phase comprises two components, namely CHs selection and cluster formation, each of which contains two sub-processes, as shown in Fig. 3.

In order to achieve energy efficiency and give consideration to QoS requirements, we take the energy level, Qos status and node's position as the main criteria. The sub-criteria are composed of residual energy, communication cost between a node and its neighbors, link quality, restart number, number of neighbors and node marginality. On the basis of the comprehensive analysis and the evaluation indices of the CH selection, the hierarchy structure is constructed as in Fig. 4. Under this hierarchy structure, the traditional weighted average method cannot be applied on account of the interdependence or interactivity among the criteria on layer C. In this case, we propose to use the MCDM approach based on trapezoidal fuzzy AHP and hierarchical fuzzy integral as the CH selection scheme.

4.1 Initialization

In a distributed network, the node elects itself to be a CH only based on local information. Therefore, it is necessary to collect the information of the neighborhood nodes within the radio coverage region of a certain transmission power level above all. Here the radio coverage region is assumed to be a circular disk, the radius of which should be optimal. We can achieve this optimal radius based on the approach mentioned in [26]. For a commercial node, the power adjustment function is indispensable. Just like the derailleur of an automobile, the transmission power of a node is also divided into several levels, and each level can cover

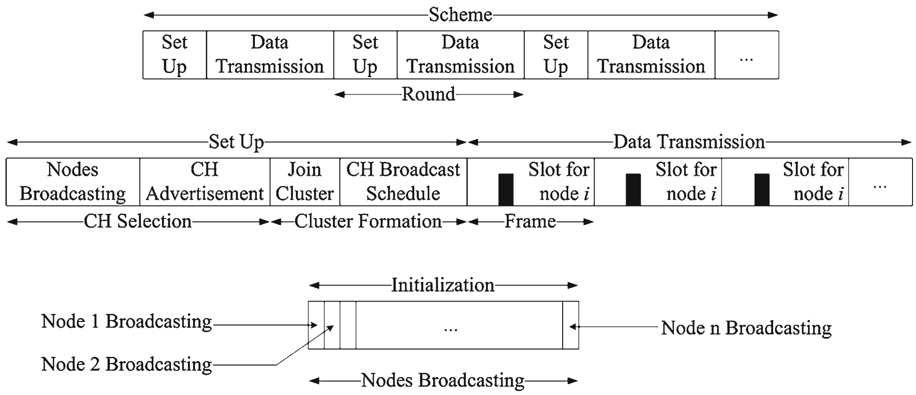

Fig. 3 Time structure diagram of FAHP scheme

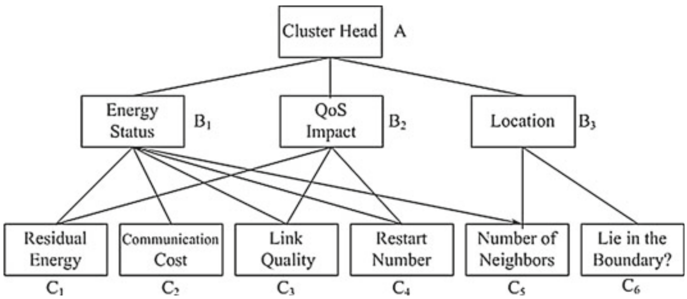

Fig. 4 Cluster head selection hierarchy structure

a roughly fixed range. Therefore, there is one to one correspondence relationship between transmission power level and coverage range. Hence, the corresponding optimal transmission power level can be obtained by looking up table or testing.

Each node broadcasts a message to its vicinal nodes in initialization (node broadcasting) phase. This message contains some information such as residual energy, coordinate, re-transmission number and restart number. If broadcasting the message spends δ seconds, on account of the assumption that all nodes are synchronized in time, each node can send the message at $ID \times \delta$ seconds in order to avoid interference and collision. Thereby the total time of initialization phase is $n \times \delta$ seconds, where n represents the total number of the nodes. The node, which receives the messages from neighbors, stores the information into memory. When initialization phase is over, each node will calculate out the maximum and minimum energy of the neighbors, the ideal and the actual communication cost between the node and the neighbors, the number of neighbors, and so on. In this way, the node can obtain all parameters it wants.

Then each node starts to compute the values of these criteria (attributes).

- Residual Energy (E)

In self-organization schemes, CHs are nodes that consume more energy than cluster members when they involve in aggregating, processing and routing data [27]. The energy is the most important and scarce resource that should be considered first in sensor networks. Generally, sensor nodes are limited in power and irreplaceable since these nodes have limited capacity and are unattended [28]. The evaluation value of residual energy is defined as follows:

$$E = \frac{E_r - E_{\min}}{E_{\max} - E_{\min}}, \tag{9}$$

where the $E_{\max}$ and $E_{\min}$ are the maximum and minimum residual energy in the neighborhood, respectively; and E_r is the residual energy of a regular node. The higher the E value is, the lesser energy-criticality the node has.

- The communication cost between a node and its neighbors (C)

From the Sect. 3.2, the free space model is used in the short-range wireless communication. As a result the energy that is consumed in transmitting a message is proportional to the square of the distance between the candidate nodes and the source node. If a node wants to be the CH, the energy used in transmitting messages will be the main communication cost. Therefore, the evaluation value of communication cost is defined as follows:

$$C = \frac{d_{\text{avg}}^2}{d_0^2}. \tag{10}$$

Here d_0 is the broadcasting radius of the node, which will be set the same in the broadcasting phase of each node. The d_{avg} denotes the average distance between the node and the neighbors. The smaller the C value is, the lower the cost of energy dissipation is.

- Link Quality (Q)

Wireless fading channel is usually random and time-variant, so that re-transmission will take place once the receiver has not parsed signal correctly. Re-transmission needs extra energy dissipation of the transmitter. Therefore, the link quality must be evaluated to achieve energy efficiency. The evaluation value of link quality is calculated through:

$$Q = \frac{Q_i - Q_{\min}}{Q_{\max} - Q_{\min}}, \tag{11}$$

where Q_i represents the total re-transmission number between the neighbors and the node, and the $Q_{\max}$ and $Q_{\min}$ are the maximum and minimum re-transmission number from the neighborhood, respectively.

- Restart number (S)

The sensor node is in fact an embedded computer system. Sometimes, the main program is likely to enter the endless loop state on account of hardware or software malfunction. In this case, the watchdog circuit would restart the computer system in order to ensure the node to continue working. However, frequent restart can consume additional energy. Thus, the more the restart number is, the more the energy consumption must be. Therefore, the evaluation value of restart number is defined as follows:

$$S = 1 - \frac{S_0 - S_{\min}}{S_{\max} - S_{\min}}, \tag{12}$$

where S_0 denotes the total restart number after the sensor network has been deployed; $S_{\max}$ and $S_{\min}$ are the maximum and minimum restart number received from neighbors, respectively.

- Number of Neighbors (D)

There is a direct relationship between the number of neighbors and CH. Theoretically, the rule is that the closer the neighbors approach the optimal number, the greater probability a node becomes a CH with. Therefore, the evaluation value of the number of neighbors is described as:

$$D = \frac{|D_i - D_0|}{D_0}. \tag{13}$$

In the equation, D_i represents the number of neighbors of the node, and D_0 is the optimal number of neighbors. When the number of neighbors is equal to the optimal number, the evaluation value of the number of neighbors should reach 1.

- Node Marginality (M)

If a node locates at the edge of the monitoring area, then part of its coverage region would have no sensor nodes. In this case, the node only covers a limited region so that the total number of CHs in the network will increase. The increment of CHs will result in redundant energy dissipation. The node marginality is defined as follows:

$$M = \frac{q}{4}, \tag{14}$$

where q indicates the quadrant number that the neighbors occupied if the node sets itself as the origin.

4.2 Determining the Grade of Criteria Importance (Weight)

The grade of criteria importance is determined from the questionnaire investigation and the mapping membership function of the five scales of linguistic variables. The judgment matrix based on trapezoidal fuzzy AHP is shown as follows:

$$\mathbf{A}-\mathbf{B}=\begin{pmatrix} (1111) & (1445) & (3667) \\ (\frac{1}{5}\frac{1}{4}\frac{1}{4}1) & (1111) & (1445) \\ (\frac{1}{7}\frac{1}{6}\frac{1}{6}\frac{1}{3}) & (\frac{1}{5}\frac{1}{4}\frac{1}{4}1) & (1111) \end{pmatrix} \tag{15}$$

$$\mathbf{B_1}-\mathbf{C}=\begin{pmatrix} (1111) & (2557) & (3778) & (3779) & (4889) \\ (\frac{1}{7}\frac{1}{5}\frac{1}{5}\frac{1}{2}) & (1111) & (2446) & (2668) & (4889) \\ (\frac{1}{8}\frac{1}{7}\frac{1}{7}\frac{1}{3}) & (\frac{1}{6}\frac{1}{4}\frac{1}{4}\frac{1}{2}) & (1111) & (1335) & (3557) \\ (\frac{1}{9}\frac{1}{7}\frac{1}{7}\frac{1}{3}) & (\frac{1}{8}\frac{1}{6}\frac{1}{6}\frac{1}{2}) & (\frac{1}{5}\frac{1}{3}\frac{1}{3}1) & (1111) & (1446) \\ (\frac{1}{9}\frac{1}{8}\frac{1}{8}\frac{1}{4}) & (\frac{1}{9}\frac{1}{8}\frac{1}{8}\frac{1}{4}) & (\frac{1}{7}\frac{1}{5}\frac{1}{5}\frac{1}{3}) & (\frac{1}{6}\frac{1}{4}\frac{1}{4}1) & (1111) \end{pmatrix} \tag{16}$$

$$\mathbf{B_2}-\mathbf{C}=\begin{pmatrix} (1111) & (1335) & (2446) \\ (\frac{1}{5}\frac{1}{3}\frac{1}{3}1) & (1111) & (1334) \\ (\frac{1}{6}\frac{1}{4}\frac{1}{4}\frac{1}{2}) & (\frac{1}{4}\frac{1}{3}\frac{1}{3}1) & (1111) \end{pmatrix} \tag{17}$$

$$\mathbf{B_3}-\mathbf{C}=\begin{pmatrix} (1111) & (1446) \\ (\frac{1}{6}\frac{1}{4}\frac{1}{4}1) & (1111) \end{pmatrix} \tag{18}$$

When AHP approach is used, it is indispensable to perform the consistency test on the trapezoidal fuzzy judgment matrix in order to ensure the veracity of ranking. Therefore, the consistency test must be performed before calculating the weight. From Eq. (15), we can deduce the following matrix.

$$\mathbf{B}=\begin{pmatrix} 1 & 4 & 6 \\ \frac{1}{4} & 1 & 4 \\ \frac{1}{6} & \frac{1}{4} & 1 \end{pmatrix} \tag{19}$$

As **B** is the judgment matrix with consistency, according to criterion, it's obvious that the trapezoidal fuzzy judgment matrix $\mathbf{A}-\mathbf{B}$ is the fuzzy judgment matrix with consistency [24,29]. So are the trapezoidal fuzzy judgment matrixes $\mathbf{B_1}-\mathbf{C}$, $\mathbf{B_2}-\mathbf{C}$ and $\mathbf{B_3}-\mathbf{C}$.

The element of the judgment matrix can be obtained from the results of pairwise comparison between criteria on the same layer. If the element of the judgment matrix is described as a trapezoidal fuzzy number (l, m, n, s), then $\alpha_i = (\prod_{j=1}^{m} l_{ij})^{\frac{1}{m}}$ and $\alpha = \sum_{i=1}^{m} \alpha_i$ can be calculated. In the above two equations, m represents the matrix order; i and j denote the criteria in pairwise comparison. Analogously, β_i, β, γ_i, γ, δ_i and δ can also be obtained. Thus, the weight of criteria on upper layer is $\left(\frac{\alpha_i}{\delta}\,\frac{\beta_i}{\gamma}\,\frac{\gamma_i}{\beta}\,\frac{\delta_i}{\alpha}\right)$. In this way, each criterion on upper layer assigns the weight to the corresponding criteria on lower layer. For example, the trapezoidal fuzzy judgment matrix $\mathbf{B_1}-\mathbf{C}$ is calculated as follows:

First of all, α_i, β_i, γ_i, δ_i need to be computed.

$$\begin{cases} \alpha_1 = \sqrt[5]{1 \times 2 \times 3 \times 3 \times 4} = 2.352 \\ \beta_1 = \gamma_1 = \sqrt[5]{1 \times 5 \times 7 \times 7 \times 8} = 4.555 \\ \delta_1 = \sqrt[5]{1 \times 7 \times 8 \times 9 \times 9} = 5.261 \\ \alpha_2 = \sqrt[5]{\frac{1}{7} \times 1 \times 2 \times 2 \times 4} = 1.179 \\ \beta_2 = \gamma_2 = \sqrt[5]{\frac{1}{5} \times 1 \times 4 \times 5 \times 8} = 2.074 \\ \delta_2 = \sqrt[5]{\frac{1}{2} \times 1 \times 6 \times 8 \times 9} = 2.930 \\ \alpha_3 = \sqrt[5]{\frac{1}{8} \times \frac{1}{6} \times 1 \times 1 \times 3} = 0.574 \\ \beta_3 = \gamma_3 = \sqrt[5]{\frac{1}{7} \times \frac{1}{4} \times 1 \times 3 \times 5} = 0.883 \\ \delta_3 = \sqrt[5]{\frac{1}{3} \times \frac{1}{2} \times 1 \times 5 \times 7} = 1.423 \\ \alpha_4 = \sqrt[5]{\frac{1}{9} \times \frac{1}{8} \times \frac{1}{5} \times 1 \times 1} = 0.308 \\ \beta_4 = \gamma_4 = \sqrt[5]{\frac{1}{7} \times \frac{1}{6} \times \frac{1}{3} \times 1 \times 4} = 0.502 \\ \delta_4 = \sqrt[5]{\frac{1}{3} \times \frac{1}{2} \times 1 \times 1 \times 6} = 1.000 \\ \alpha_5 = \sqrt[5]{\frac{1}{9} \times \frac{1}{9} \times \frac{1}{7} \times \frac{1}{7} \times 1} = 0.197 \\ \beta_5 = \gamma_5 = \sqrt[5]{\frac{1}{8} \times \frac{1}{8} \times \frac{1}{5} \times \frac{1}{4} \times 1} = 0.239 \\ \delta_5 = \sqrt[5]{\frac{1}{4} \times \frac{1}{4} \times \frac{1}{3} \times 1 \times 1} = 0.461 \end{cases} \tag{20}$$

Based on the values above, α, β, γ, δ are obtained.

$$\begin{cases} \alpha = \alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 + \alpha_5 = 2.352 + 1.179 + 0.574 + 0.308 + 0.197 = 4.610 \\ \beta = \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 = 4.555 + 2.074 + 0.883 + 0.502 + 0.239 = 8.253 \\ \gamma = \gamma_1 + \gamma_2 + \gamma_3 + \gamma_4 + \gamma_5 = 4.555 + 2.074 + 0.883 + 0.502 + 0.239 = 8.253 \\ \delta = \delta_1 + \delta_2 + \delta_3 + \delta_4 + \delta_5 = 5.261 + 2.930 + 1.423 + 1.000 + 0.461 = 11.075 \end{cases} \tag{21}$$

In this way, we can achieve the fuzzy weights—ω_1, ω_2, ω_3, ω_4, ω_5, which are the weights of guide line layer criteria C_1, C_2, C_3, C_4 and C_5 to the general evaluating target B_1, respectively.

$$\begin{cases} \omega_1 = \left(\frac{\alpha_1}{\delta}\ \frac{\beta_1}{\gamma}\ \frac{\gamma_1}{\beta}\ \frac{\delta_1}{\alpha}\right) = \left(\frac{2.352}{11.075}\ \frac{4.555}{8.235}\ \frac{4.555}{8.235}\ \frac{5.261}{4.610}\right) = (0.212\ \ 0.552\ \ 0.552\ \ 1.141) \\ \omega_2 = \left(\frac{\alpha_2}{\delta}\ \frac{\beta_2}{\gamma}\ \frac{\gamma_2}{\beta}\ \frac{\delta_2}{\alpha}\right) = \left(\frac{1.179}{11.075}\ \frac{2.074}{8.235}\ \frac{2.074}{8.235}\ \frac{2.930}{4.610}\right) = (0.106\ \ 0.251\ \ 0.251\ \ 0.636) \\ \omega_3 = \left(\frac{\alpha_3}{\delta}\ \frac{\beta_3}{\gamma}\ \frac{\gamma_3}{\beta}\ \frac{\delta_3}{\alpha}\right) = \left(\frac{0.574}{11.075}\ \frac{0.883}{8.235}\ \frac{0.883}{8.235}\ \frac{1.423}{4.610}\right) = (0.052\ \ 0.107\ \ 0.107\ \ 0.309) \\ \omega_4 = \left(\frac{\alpha_4}{\delta}\ \frac{\beta_4}{\gamma}\ \frac{\gamma_4}{\beta}\ \frac{\delta_4}{\alpha}\right) = \left(\frac{0.308}{11.075}\ \frac{0.502}{8.235}\ \frac{0.502}{8.235}\ \frac{1.000}{4.610}\right) = (0.028\ \ 0.061\ \ 0.061\ \ 0.217) \\ \omega_5 = \left(\frac{\alpha_5}{\delta}\ \frac{\beta_5}{\gamma}\ \frac{\gamma_5}{\beta}\ \frac{\delta_5}{\alpha}\right) = \left(\frac{0.197}{11.075}\ \frac{0.239}{8.235}\ \frac{0.239}{8.235}\ \frac{0.461}{4.610}\right) = (0.018\ \ 0.029\ \ 0.029\ \ 0.100) \end{cases} \tag{22}$$

Table 1 The grade of criteria importance based on trapezoidal fuzzy AHP

Attribute	B_1	B_2	B_3	The grade of criteria importance
	0.6315	0.3263	0.0422	
C_1	0.5666	0.5564	0	0.5394
C_2	0.3314	0	0	0.2093
C_3	0.1014	0.3273	0	0.1708
C_4	0.0006	0.1163	0	0.0383
C_5	0	0	0.7081	0.0299
C_6	0	0	0.2919	0.0123

If $M = (r_1 \ \ r_2 \ \ r_3 \ \ r_4)$ and $N = (s_1 \ \ s_2 \ \ s_3 \ \ s_4)$ are two trapezoidal fuzzy numbers, then the possibility of $M \geqslant N$ is:

$$V(\omega_M \geqslant \omega_N) = \begin{cases} 1 & r_3 \geqslant s_2 \\ \frac{r_4 - s_1}{(r_4 - r_3) + (s_2 - s_1)} & r_3 \leqslant s_2, \quad r_4 \geqslant s_1 \\ 0 & r_4 \leqslant s_1 \end{cases} \tag{23}$$

According to the equation above, we can obtain follows.

$$\begin{cases} V(\omega_1 \geqslant \omega_2) = 1, V(\omega_2 \geqslant \omega_1) = 0.585 \\ V(\omega_1 \geqslant \omega_3) = 1, V(\omega_3 \geqslant \omega_1) = 0.179 \\ V(\omega_1 \geqslant \omega_4) = 1, V(\omega_4 \geqslant \omega_1) = 0.01 \\ V(\omega_1 \geqslant \omega_5) = 1, V(\omega_5 \geqslant \omega_1) = 0 \\ V(\omega_2 \geqslant \omega_3) = 1, V(\omega_3 \geqslant \omega_2) = 0.585 \\ V(\omega_2 \geqslant \omega_4) = 1, V(\omega_4 \geqslant \omega_2) = 0.369 \\ V(\omega_2 \geqslant \omega_5) = 1, V(\omega_5 \geqslant \omega_2) = 0 \\ V(\omega_3 \geqslant \omega_4) = 1, V(\omega_4 \geqslant \omega_3) = 0.782 \\ V(\omega_3 \geqslant \omega_5) = 1, V(\omega_5 \geqslant \omega_3) = 0.381 \\ V(\omega_4 \geqslant \omega_5) = 1, V(\omega_5 \geqslant \omega_4) = 0.692 \end{cases} \tag{24}$$

The single sequencing of each factor on layer k to A_h^{k-1} is calculated as follows:

$$P_h^k(A_i^k) = \min_j \quad V(\omega_{ih}^k \geqslant \omega_{jh}^k), \tag{25}$$

where h represents the total factors related to the target A_h^{k-1}. After the unification processing that is based on the two equations mentioned above, we get the crisp weight

$$W_i = \left(P_h^k\left(A_1^k\right), P_h^k\left(A_2^k\right), \ldots, P_h^k\left(A_{n_k}^k\right)\right) = \sum_{i=1}^{n_k} P_h^k\left(A_i^k\right). \tag{26}$$

In terms of this equation, the crisp weight which represents the criteria C_1, C_2, C_3, C_4 and C_5 to the general evaluating target B_1 is

$$W_1 = (0.5666, 0.3314, 0.1014, 0.0006, 0). \tag{27}$$

The other weights can be obtained in the same way, and the results are shown in Table 1.

4.3 Fuzzy Integral for Evaluating the Nodes

After constructing a hierarchical multi-attributes evaluation system, fuzzy integral is applied to gain a composite value based on Eq. (8). In Fig. 4, since the evaluation system of the CHs constructs a tree hierarchy, the evaluation values are investigated from the bottom of the tree. Based on the values of the criteria in Sect. 4.1 and the grades of importance in Table 1, the overall evaluation of the node is obtained by determining the grades of importance, assessment scores and hierarchical structure of the fuzzy integral in Sect. 3.3.3.

4.4 Cluster Head Selection

Each node has obtained the composite value f in Sect. 4.3, then the next task is how to relate this composite value to the CH election. For the reason that the probability that the grade of criteria importance and the evaluation value are exactly same is little, it is almost impossible that the composite value f takes the same value. The node whose composite value f is bigger has higher probability of being the CH than the smaller one, because the former has a great advantage over the latter in the energy efficiency. Then the composite value f is mapped onto the time axis before the CH broadcasts by means of the timer triggering, from which the node whose composite value is bigger broadcasts CH information earlier.

A time T_i, whose time span is determined by the composite value f, is set for each node. For the reason that the node whose composite value is bigger broadcasts CH information at the earlier time, the equation below is available:

$$T_i = (1 - f) \times T', \tag{28}$$

where T' is the total time in which all CHs broadcast information. However, data packets' collisions are inevitable in case the nodes that hold the same composite value in the network implement the simultaneous CH broadcasting. To avoid this, a random number between 0 and 1 is introduced to generate disturbance. A constant λ is set to be 0.9, by which the relationship between T_i and the composite value f would not be affected. Thus the improved equation is described here.

$$T_i = \{1 - [\lambda \times f + (1 - \lambda) \times \text{rand}(0, 1)]\} \times T' \tag{29}$$

The Eq. (29) makes the composite value mapped onto the time axis. Timer overtime, a CH advertisement packet is broadcasted at the optimal radius by the CH node. The nodes that can receive and parse this packet correctly will lose the chance of being the CHs if the sender is lying in the neighbor list that stored in memory, which is called "first declaration wins" [30]. That is, the sender utilizes radio signal to control the receiver's action, so the node that broadcasts the radio signal earliest in the vicinity can dictate the receiver to cancel the sending behavior of this time. Thus, the node that can broadcast CH advertisement earliest becomes the CH, while the other nodes in the vicinity only act on member nodes. This rule makes the CHs distribute evenly in the entire network because the distance between any two CHs exceeds the optimal radius.

The CH broadcasting is finished while T' is over.

Algorithm 1 Clustering

```
if broadcastingTime then
    send(ID, E_r, RS_n, RT_n, X, Y) // RS_n represents restart number
                                       while RT_n indicates re-transmission number.
                                    // X, Y is the coordinate of the node.
else
    receive(ID, E_r, RS_n, RT_n, X, Y)
end if
trapezoidal fuzzy judgement matrix construction based on questionnaire investigation
the consistency test
calculate the composite value f of the evaluating criteria
T_i ← (1 − (0.9 × f + 0.1 × rand(0, 1))) × T'
if no CH advertisement was received && T_i time out then
    broadcast (CH)
    headFlag ← 1
end if
if total advertisementTime time out then
    myCH ← selectBest(CH)
    join(myCH)
end if
if headFlag == 1 then
    createTDMA()
    broadcast(TDMA)
else
    receive(TDMA)
end if
```

4.5 Cluster Formation

On receiving the advertisement of CHs, the member nodes select the nearest CH and reply to a Join packet back to the corresponding CH using the CSMA MAC protocol. The distance between the member node and the corresponding CH is evaluated as well.

At the sensor node level, the sensors can be scheduled to sense the environment at different samples or time intervals and sleep as much as possible in order to conserve battery power. Although some information might be lost, this is an effective way to optimize energy consumption [31].

If the distance between the member node and the CH is more than its distance to the BS, the member node will communicate with the BS directly at a fixed time slice regardless of corresponding CH while go to dormancy at the rest time to save energy.

The CH assigns a time slot for each member after receiving all join information, by which a TDMA schedule is schemed to indicate when each member in the cluster can transmit. Then the schedule is broadcasted back to the members in the cluster.

As only the CH selection scheme is investigated in this paper, the inter-cluster route is not mentioned here.

To reduce inter-cluster interference, the usage of a DSSS PHY will be adopted in FAHP. Each cluster in FAHP communicates using DSSS(direct-sequence spread spectrum). Each cluster uses a unique spreading code, so that all the nodes in the cluster transmit their data to the CH using this spreading code and the CH filters all received signals using this spreading code. With enough spreading, neighboring clusters' radio signals will be filtered out as noise during de-correlation and not corrupt the transmission from nodes in the cluster.

Table 2 Parameters in simulation

Parameters	Value
Simulation area (m)	100×100
BS location	(50,175)
Initial energy (J)	2
Data packet size (bytes)	500
Threshold distance (m)	86
Packet header size (bytes)	25
E_{elec} (nJ/bit)	50
E_{fusion} (nJ/bit/signal)	5
ε_{fs} (pJ/bit/m^2)	10
ε_{mp} (pJ/bit/m^4)	0.0013
Round(second)	20

4.6 Data Transmission

At data transmission phase, the member nodes collect data and send information to the CH in the scheduled transmission time, and then turn off the radio. Based on the received signal strength of the CH advertisement and the assumption of the symmetrical radio channel, the transmission can use a minimum amount of energy. The CH must keep a working state to receive the information come from its members. When a frame of data from all the members is received, the CH applies data fusion to aggregate the received data into a single packet. Then the CH sends the aggregated data to the BS directly.

5 Simulations and Analysis

5.1 The Selection of Simulation Platform

NS2 is adopted as the simulation platform in this paper. NS2 is a discrete event simulator, in which the object oriented design technique is introduced as well as plenty of function models are furnished. It can simulate and analyze various networks' protocols, and can draw scientific conclusions about the performance analysis of the system.

LEACH, DCHS, and CHEF are simulated and compared with FAHP in the same scenario, as the parameters are set in Table 2.

We executed 20 runs of the simulation for each of the four clustering algorithms that need to be compared. The readings from these 20 trials were then averaged and plotted. The simulation results are described in Figs. 5, 6, 7 and 8.

5.2 Performance Analysis

Figure 5 shows the number of nodes alive over runtime, from which it is obvious that the whole lifetime of FAHP increases twice approximately more than that of LEACH on the total runtime of the entire network, as well as 50% and 30% more than that of DCHS and CHEF, respectively. The time of the first dead node is at 390th second in FAHP while the 210th, 270th and 310th second are available in LEACH, DCHS and CHEF algorithms, which is a

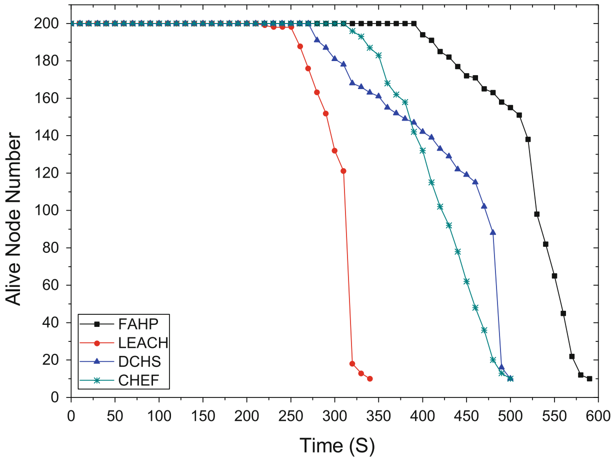

Fig. 5 Alive nodes comparison diagram for 200 nodes

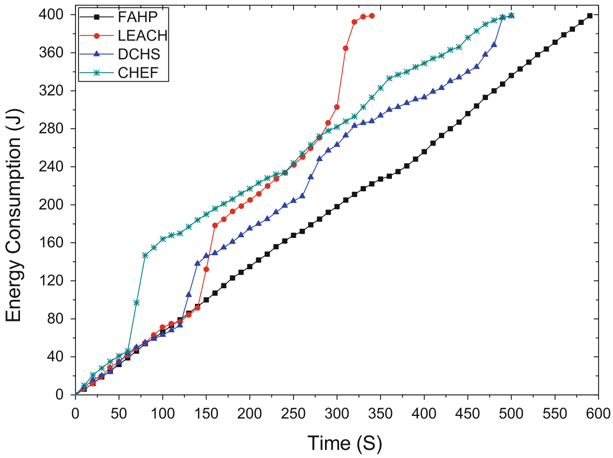

Fig. 6 Energy analysis chart for 200 nodes

great improvement. LEACH algorithm selects CHs assuming that each time a node becomes a CH it dissipates the same amount of energy. This leads to inefficient selection of heads towards the end of simulation thereby depleting the network fast. DCHS and CHEF improve the performance by introducing some attributes into the algorithms. DCHS takes energy as metric while CHEF takes energy and local distance into account, hence the lifetime of them is longer than that of LEACH. However, FAHP not only takes more attributes into account, but also handles the non-linear relationship properly, thereby the longevity is achieved. In addition, the optimal broadcasting radius is adopted to reduce the energy consumption of the entire network, which makes the energy of each node be saved and be used efficiently, so that a substantial increase in the network lifetime is expected.

Figure 6 demonstrates the energy consumed by all nodes during the simulation runs. As expected, FAHP adopts the rule "first declaration wins" resulting in evenly distributed clusters. As a consequence, energy dissipation in FAHP occurs at a lower rate than the other

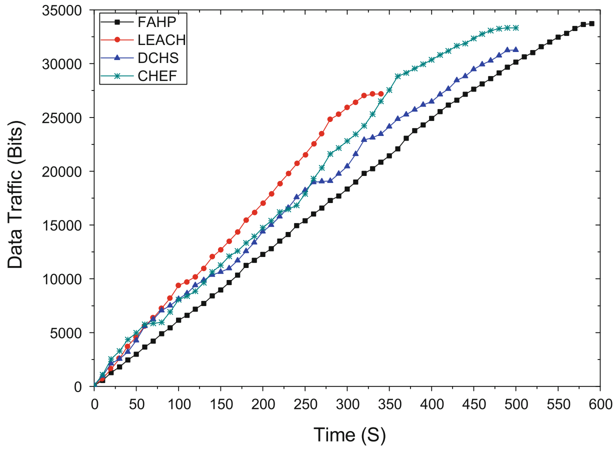

Fig. 7 Traffic comparison diagram for 200 nodes

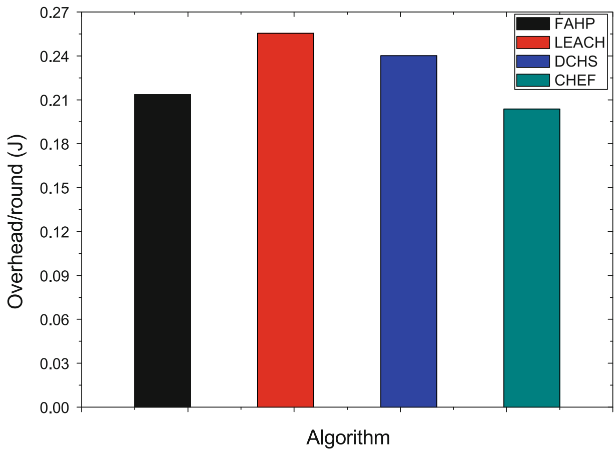

Fig. 8 Overhead within each round among the four algorithms for 200 nodes

algorithms. The simulations show that FAHP scheme have consumed similar energy at each round during the network operation while the different energy dissipation at each round in the other algorithms, which demonstrates that our proposed scheme is able to keep a stable trend in energy dissipation as the round increasing while there are sudden increments during implementing the other algorithms. From the energy consumption in one round of the four algorithms, FAHP achieves an improvement of 20% more than DCHS, 35% more than LEACH and CHEF, as described in Fig. 6. In 0–50 or even 100 s, the energy consumption in FAHP is basically consistent with the classic algorithms. It should be said that the unexpected is reasonable, because from the appearance FAHP requires multiple communications during neighbor information collection, which should consume more energy than the classical algorithms. However, FAHP uses lower optimal transmission power level instead of maximum transmission power in the other algorithms, which can reduce part of the energy consumption. In addition, the control message in the neighbor information collection process is much shorter than the data packet, so that compared to the energy consumption of data packet, the energy dissipation of the control message can almost be ignored. Therefore, in the beginning, FAHP achieves similar energy consumption as the other algorithms.

The traffic to the BS plotted against simulation time is illustrated in Fig. 7, from which it is indicated that the total number of packets delivered to the BS is cumulative and steadily increases as we increase the simulation time. The gradual decrease of the slope of the curve towards the end of simulation is because the nodes are failing as the simulation progresses in time. Our results also indicate that the traffic of FAHP is somewhat less than that of the other algorithms. This is mainly due to the fact that FAHP requires multiple control message interactions in order to collect attributes, which occupies some data communication time so that the total traffic decrease. Our results show that the total number of packets reaches nearly 35,000 in FAHP while this value cannot reach 35,000 in the other algorithms. Moreover, the cluster heads are chosen randomly in LEACH, while FAHP makes cluster heads evenly distributed. This reduces the energy loss due to transmission for the nodes expected to transmit frequently, thereby delivering the same amount of data with less energy dissipation.

LEACH, DCHS, CHEF and FAHP belong to active clustering algorithms. The common feature of this kind of algorithm is that control messages are required to exchange information among neighboring nodes to select CHs, as a result considerable overhead will be generated. From Fig. 8 we can observe that FAHP generates similar overhead to the other algorithms in each round. This is a very interesting phenomenon because FAHP uses more control messages than the other algorithms, especially in all nodes' broadcasting attributes information. The reason for the phenomenon above is that FAHP sends messages only at the optimal transmission power, while the maximum transmission power is used in the other algorithms, which result in excessive energy is consumed. For example, if n sensor nodes are evenly distributed in the whole network, then FAHP will send n control messages more than the other algorithms. At the same time, if the optimal number of cluster heads is k, each node will receive about $n/k-1$ control messages. Thus FAHP will receive $n \times (n/k - 1)$ control messages more than the other algorithms. Assumed that the largest communication distance is 135 m, and the optimal one is 25 m, which also used in simulation, then according to the wireless channel model defined in Sect. 3.2 and the parameters in Table 2, the energy consumption of the maximum transmission power level is $50 + 0.0013 \times 135^4 \times 10^{-3} = 481.7958$ nJ/bit while the energy consumption of the optimal transmission power level is $50 + 10 \times 25^2 \times 10^{-3} = 56.25$ nJ/bit. In LEACH algorithm, maximum transmission power level is used in the process of the CH advertisement and member nodes joining cluster, so the energy used in these two periods is $k \times 8 \times 481.7958 + (n-k) \times 8 \times 481.7958 = 3854.3664\,n$nJ, in which the decimal digit "8" represents the bits that each information occupied. Similarly, the energy consumed in the process of the node broadcasting, CH advertisement and member nodes joining cluster of FAHP is $6 \times 8 \times n \times 56.25 + k \times 8 \times 56.25 + (n-k) \times 8 \times 56.25 = 3150\,n$nJ. Therefore, although the control message of our proposed scheme is more, there is still no major increase in the overhead of our proposed scheme.

5.3 Complexity Analysis

Time complexity is a significant indicator to any algorithm. In the scheme described in Sect. 4, the sensors elect themselves as CHs and join a cluster independent of each other. Hence, the algorithm can utilize opportunities for concurrency in communication. The run-time of the algorithm is the time to transmit a message from a member node to the CH of its cluster. Since the members in a cluster are at most one hop away from the corresponding CH, the time complexity of the proposed scheme to generate a clustering hierarchy is $O(1)$ in a contention-free environment. In an environment where there is contention for media access, the complexity of FAHP will depend on the underlying MAC protocol. For any reasonable MAC protocol, the complexity will be much lower than $O(n)$, where n is the number of nodes in the network [32]. This makes our proposed scheme more suitable for large-scale networks.

As a resource-limited system, message complexity is also important in wireless sensor networks. It is assumed that there are nodes in the network, and the nodes broadcast $n\langle ID, E_r, RS_n, RT_n, X, Y\rangle$ messages during the CHs selection, followed by k CHs broadcasting if k CHs are selected all over the network. Then $n-k$ join messages are broadcasted by all member nodes. Furthermore, k CHs will broadcast at most k TDMA schedule subsequently. Thus, the total message spending in the phase of a cluster forming is $n+k+n-k+k = 2n+k$ in the whole network, which denotes that the message complexity of FAHP in the setup phase is $O(n)$.

6 Conclusions

Cluster head selection scheme is an important research issue, which will also influence the operational efficiency of network. On the basis of analysis and comparison of some classical algorithms, a novel MCDM CH selection scheme is proposed. The trapezoidal fuzzy AHP and hierarchical fuzzy integral is introduced into the scheme in order to make the most criteria that can influence energy efficiency become a single one to determine the selection of the CHs, which is the main innovation and improvement of the classical algorithms. Moreover, the new scheme supports data fusion at CHs, which can eliminate the redundant data effectively so as to reduce the traffic and save the energy. The simulation results demonstrate that the lifetime and energy efficiency of FAHP is better than the classical algorithms. In addition, the rule that "first declaration wins" is introduced into the CH advertisement in order to achieve a better cluster head distribution all over the network.

Although improvements are made in some performance, there are some limits, e.g. time synchrony and fault tolerant, in using this algorithm yet. FAHP belongs to the active clustering algorithm so that this scheme is most appropriate when constant monitoring by the sensor network is needed.

In further work, the spare CH scheme should be introduced to promote the robustness.

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