

An Improved Genetic Algorithm Based Annulus-sector Clustering Routing Protocol for Wireless Sensor Networks

Wang Chu-hang

Changchun Normal University

Liu Xiao-li

Changchun Normal University

Youjia Han (✉ 364517162@qq.com)

Changchun University of Technology

Hu Huang-shui

Changchun University of Technology

Wu Sha-sha

Changchun University of Technology

Research Article

Keywords: Wireless sensor networks, Annulus-sector, Genetic algorithm, Optimal routing paths, Energy and load balance

Posted Date: March 23rd, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-178344/v1>

License:  This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Version of Record: A version of this preprint was published at Wireless Personal Communications on November 2nd, 2021. See the published version at <https://doi.org/10.1007/s11277-021-09306-1>.

An Improved Genetic Algorithm Based Annulus-sector Clustering Routing Protocol for Wireless Sensor Networks

Wang Chu-hang¹ · Liu Xiao-li¹ · Han You-jia² · Hu Huang-shui² · Wu Sha-sha²

Abstract

In wireless sensor networks, uniform cluster formation and optimal routing paths finding are always the two most important factors for clustering routing protocols to minimize the network energy consumption and balance the network load. In this paper, an improved genetic algorithm based annulus-sector clustering routing protocol called GACRP is proposed. In GACRP, the circular network is divided into sectors with the same size for each annulus, whose number is determined by calculating the minimum energy consumption of each annulus. Each annulus-sector forms a cluster and the best node in this annulus-sector is selected as cluster head. Moreover, an improved genetic algorithm with a novel fitness function considering energy and load balance is presented to find the optimal routing path for each CH, and an adaptive round time is calculated for maintaining the clusters. Simulation results show that GACRP can significantly improve the network energy efficiency and prolong the network lifetime as well as mitigate the hot spot problem.

Keywords Wireless sensor networks, Annulus-sector, Genetic algorithm, Optimal routing paths, Energy and load balance

1 Introduction

With the rapid development of artificial intelligence and internet of things (IOT), wireless sensor networks (WSNs) are being widely used for information collection from various applications such as health and environment monitoring, battlefield surveillance and space exploration [1]. Saving energy consumption to prolong the network lifetime is always the eternal theme because the nodes in these networks are resource constrained and often randomly deployed in harsh environments. Clustering routing have been proved to reduce energy consumption, improve network scalability as well as extend the network lifetime [2,3], and many approaches have been proposed during the last decades, which usually consists of two phases: cluster construction and data delivery. In the phase of cluster construction, cluster heads (CHs) are selected by random probability based [4,5], weight based [6,7], intelligent computing based [8,9] methods. And single-hop [4], multi-hop [5,7-9] or hybrid [6] schemes are used for data transmission during the data delivery phase. All the existing approaches can reduce network energy consumption and prolong the network lifetime to a certain extend. However, neglecting of the clusters' size results in uneven clusters, and the random distribution of clusters is most likely to cause unbalanced energy consumption. What's more, long distance transmission existing in the routing paths exponentially increases the energy consumption.

Clustering routing approaches dividing the sensing area into annular sectors have been presented to solve the problem mentioned above [10,11]. Usually, the size of each annulus-sector is the same and the nodes in each annulus-sector form a cluster so as to balance the energy consumption because they consume roughly the same amount of energy for their almost same distance to the BS. And the best node in each annulus-sector is selected as CH so as to decrease the amount of interaction based on probability [12], weight according to residual energy [13], residual energy and distance to the BS [11], residual energy and distance to the center of the cluster [10], received signal strength [14]. Moreover, a multi-hop data delivery scheme is used to make CHs located in an outer annulus forward data to one CH lying in its next annulus till to the BS in order to improve the energy efficiency and reduce the network energy consumption. In this way, the nodes near the BS deplete their energy much quicker than the others due to the data traffic gathered in the BS, resulting in unbalanced load and uneven energy consumption across the network, which is typically known as the hot spot problem [15]. Various unequal clustering approaches have been proposed to solve the hot spot problem in traditional hierarchy networks [16]. For circular networks, different size of annulus-sector division or specific data forwarding scheme is utilized for load balancing among the CHs so as to alleviate the hot spot problem [10-12]. However, that the number of sectors is randomly divided makes it impossible for uniform energy consumption in each annulus. Furthermore, hop-by-hop data delivery burdens the intermediate nodes which are prone to premature death. Especially, fixed round time based maintaining the clusters produces too much overhead due to the frequent CHs rotation.

In this paper, an improved genetic algorithm based annulus-sector clustering routing protocol (GACRP) is proposed to minimize the

* Corresponding author: Han You-jia (E-mail: 364517162@qq.com).

¹College of Computer Science and Technology, Changchun Normal University, Changchun, 130032, China

² College of Computer Science and Engineering, Changchun University of Technology, Changchun, 130012, China

network energy consumption and balance the network load. The circular network is firstly divided into different annulus, and each annulus is separated into different sectors with the same size according to the calculated optimal number of clusters, and a CH is selected in each cluster according to its load, residual energy and distance to the BS. Moreover, an improved genetic algorithm is used to find the optimal routing path for each CH so as to achieve load and energy balance, and a new adaptive round time is calculated for maintaining the clusters. Simulations are conducted to verify the performance of GACRP compared with several up-to-date existing relevant protocols. The main contributions are outlined as follows:

- Based on minimizing the energy consumption of each annulus, the optimal cluster number in each annulus is obtained to form uniform clusters.
- An improved genetic algorithm whose novel fitness function considers not only the minimum network energy consumption but also the balance of CHs' loads so as to find the optimal routing paths. Specifically, the routing paths are denoted by a chromosome with valid genes.
- An adaptive round time considering load and energy balancing is used for CHs rotation to avoid frequent clustering so as to further save the network energy consumption as well as improve the network throughput.

The rest of the paper is organized as follows. The related works are described in Section 2, and the network model is given in Section 3. In Section 4, the proposed GACRP is introduced in detail. In Section 5, simulations are conducted to verify the effectiveness of GACRP. Finally, conclusions are drawn in Section 6.

2 Related works

Clustering routing approaches have been proved to efficiently extend the network lifetime with many advantages such as good scalability, high energy efficiency, low end-to-end delay, and diversified number of clustering routing schemes have been proposed during the last decades. Low-Energy Adaptive Clustering Hierarchy (LEACH) [4] is the pioneering clustering routing protocol in which CHs are selected randomly and all the nodes get selected as CHs for at least once in a certain round. Moreover, each cluster member (CM) sends its sensed data in allotted timeslot to its CH, and the CH aggregates the collected data and send it to the BS directly. Although LEACH has the advantages of simplicity, distribution, balanced load, low overhead and configurable number of CHs, its direct communication between CHs and the BS makes the farther CHs deplete energy at a faster rate, resulting in weak scalability. More importantly, selecting CHs randomly and neglecting their energy lead to distribute CHs unevenly and select the nodes with low energy as CHs, resulting in unbalanced energy consumption and nodes' premature death. In order to solve the drawbacks of LEACH, various and diverse improvements have been presented [17,18]. In [18], a survey on successors of LEACH is given according to single-hop and multi-hop communication, moreover, the advantages and the disadvantages of each variant of LEACH are described. However, traditional approaches are unable to adapt to network uncertainties and dynamics, especially to achieve the global optimal solution. Therefore, intelligent computing based methods such as bat algorithm [19], fuzzy logic control [20] and genetic algorithm [21] are proposed to solve these problems. In [19], bat algorithm is used for CH selection, which is responsible for optimizing the objective function of a cluster whose value is decided by the parameters of the average energy and the distance variance within the cluster. In [20], two fuzzy logic controllers are used to select the CHs and determine the best forwarders based on residual energy, weight, the space to the BS, distance and trust factor respectively. The outputs of the fuzzy logic controllers are the probability of being selected as CH, radius of the cluster, and the probability of being selected as the optimal forwarder. In [21], genetic algorithm is used to selects CHs, whose fitness function is computed by using parameters such as energy of all nodes, energy of CHs, distance of CH with its associated nodes, number of nodes in cluster and so on. The simulation results have verified that the aforementioned methods can form optimal clusters and obviously reduce energy consumption as well as enhance the network lifetime. However, communication in multi-hop mode among CHs inevitably makes the CHs in the vicinity of the BS take more data relay tasks and lose more energy compared to the father ones, which causes hot spot problem. Then unequal clustering routing algorithms are proposed to solve this problem by assigning the smaller cluster size for CHs nearer to the BS [22,23]. In [22], EADUC is proposed to select CHs based on the ratio of average energy of neighbor nodes and residual energy of the node itself. Especially, node degree, residual energy and distance to BS are used to calculate the competition radius, and residual energy is used as relay metric for selecting the relay nodes while the same clustering is performed for several rounds to eliminate re-clustering overhead and minimize energy consumption. In [23], DUCF assigns maximum limit of number of members for a CH based on its residual energy, node degree and distance to BS by a fuzzy output variable 'size' in order to balance the energy consumption. Moreover, DUCF uses the second fuzzy output variable 'chance' with the same inputs as 'size' for selecting the CHs so as to make the node with higher 'chance' value than its neighbors select itself as

CH. Also, a CH will check its 'size' for acceptance of new members when receiving a joining message. Furthermore, a multi-hop data transmission scheme is used to reduce energy consumption for inter-cluster communication. EADUC and DUCF perform well to extend the network lifetime. However, clustering with different size leads to unbalanced intra-cluster energy consumption, and inter-cluster communication still in hop-by-hop mode increases the routing energy consumption. Accordingly, a genetic algorithm improved multi-hop clustering routing protocol named OMPFM is proposed in [24] to find the optimal paths from the source CHs to the BS. OMPFM defines a new fitness function which considers the following four parameters: the average distance from the source CH and the BS through the intermediate CHs, the number of CHs through the path, the total number of participation in the transmission process of all CHs in the path, and the total number of member nodes in all clusters that are related to the CHs in the path. The simulation results show that OMPFM is better than the LEACH protocol in terms of the network lifetime and power consumption by approximately 50%. However, invalid individuals may be generated in OMPFM because of its adopted traditional selection, crossover and mutation operations, resulting in local optimum. Especially, forming clusters still by message broadcasting increases the network energy consumption.

Therefore, annulus-sector based clustering routing approaches have been proposed to solve the problems mentioned above, which divide the network into annular sectors, and the nodes in each annulus-sector are grouped into a cluster, which doesn't require nodes to form clusters by broadcasting so the energy consumption of nodes is reduced significantly [25, 26]. In [25], a clustering routing method for circular network has been proposed, and the optimal width between the adjacent rings is fully investigated. In addition, each CH sends its data to the BS in multi-hop mode by using its upper CHs located in the interior annulus so as to reduce energy consumption. In [26], OCCN is proposed to divide the network into concentric rings with the same width like in [25]. The optimal number of clusters k in the network is calculated to minimize the energy consumption, and the average cluster size can be described by N/k , where N is the total number of nodes in the network. Moreover, each node in a cluster reserves special sets of time slots for being CH rotated to avoid CH selection which is an energy and time consuming procedure. The upper CH toward the BS is found to relay data based on the distance to the BS. However, neglecting the residual energy, location and other parameters, the CH rotated only by the allocated timeslots in the cluster will result in uneven energy consumption and premature death of node in the cluster. Besides, the hot spot problem doesn't be considered. In [13], TSTCS divides the network into n rings and six sectors, the angle of each sector is $\pi/6$. At the same time, each sector is separated into cells with the same size. Moreover, the number of the cells in a sector increases by 1 with the *ringID* from the inner ring to the outer ring. Each cell represents a cluster, node with the highest residual energy is selected as CH in a circular region with diameter R at the middle of the cell which collects data from its members, aggregates and sends it to the BS either directly (for clusters in the closest ring to BS) or through other CHs in inner rings. Moreover, when the CH attains the preset threshold value of the residual energy, a substitution node will be selected as CH from its own R based on the energy level to provide local remedy for energy suffering. For data forwarding, the CH chooses a CH from its lower ring with higher lifetime which is defined based on average residual energy of R nodes and energy required to process the data gathering and forwarding. However, deterministic sector partition (fix angle of sector equals $\pi/6$) and number of cells (ranged from 1,2,... with the increase of *ring ID*) can't guarantee the minimum energy consumption of the network. Moreover, the value of R is not given clearly in this paper, which is likely to increase the energy consumption of each cluster. To solve this problem, AEBDC is proposed in [10] to improve the performance of TSTCS. At first, AEBDC divides the network into several annular sectors of different size, nodes in the same annulus-sector form a cluster. Then, the region for candidate CHs (RCCH) is set to effectively balance the energy consumption as well as prolong the lifetime of the clusters, which locates at the intersection of its symmetry axis and the middle line of this area. The radii of the RCCH is formulated in the paper. The nodes are located in RCCH are regarded as "candidate cluster headers (CCHs)", otherwise, "common nodes (CNs)". Furthermore, CCH with higher weight by consideration of residual energy and distance to the center of the RCCH. Especially, the CH in k annulus forwards data to the CCH with the highest residual energy in the $k-1$ annulus, and the CCH in the $k-1$ annulus forwards the data to the CCH with the highest residual energy in the $k-2$ annulus, until the BS in the end. AEBDC can effectively balance the energy consumption of the network as well as eliminate the hot spot problem. However, the farther ring from the BS and the farther distance from the RCCH for the CNs mean the more energy consumption and the easier to premature death. What is more, the nearer ring to the BS for clusters produces more links for data forwarding, which undoubtedly leads to more collisions and thus increases energy consumption. All above mentioned schemes forward data in multi-hop mode with hop-by-hop undoubtedly increase end-to-end delay as well as energy consumption, and fixed round based re-clustering produces too much overhead due to periodic formation of clusters. The main objective of this paper is to minimize the energy consumption and balance the network load by finding an optimal multi-hop routing path from every source CH to the BS.

3 Network Model

In GACRP, the network is regarded as a circular region with radius R similar to [10,13], and divided into n annulus with the same width, nodes are spatially scattered across the sensing field, the BS is located in the center of the region. Moreover, the network is assumed to have the following attributes:

- There are N nodes in the network and each node has a unique ID , the set of nodes in the network is represented as $S=\{S_1, S_2 \dots S_n\}$.
- The nodes are static and their locations can be obtained by a positioning system or an energy-efficient positioning algorithm.
- Each node has the same initial energy for being homogeneous except for the BS.

The same first order radio energy model as in [4,10,13,24] is used in this paper. The energy consumption for l – bits data transmission between two adjacent nodes with distance d can be calculated as follows:

$$E_{tx} = \begin{cases} l * E_{elec} + l * \epsilon_{fs} * d^2 & d < d_0 \\ l * E_{elec} + l * \epsilon_{mp} * d^4 & d \geq d_0 \end{cases} \quad (1)$$

where E_{elec} is the energy consumption for transmitting or receiving 1-bit data, ϵ_{fs} and ϵ_{mp} are amplifier coefficients of free space and multi-path fading respectively, d_0 is the threshold distance given by $d_0 = \sqrt{\epsilon_{fs}/\epsilon_{mp}}$.

The energy consumption of receiving l – bits data is:

$$E_{rx} = l * E_{elec} \quad (2)$$

The energy consumption of l – bits data aggregation is:

$$E_{DA} = l * E_{pDb} \quad (3)$$

where E_{pDb} is the energy consumption for 1-bit data fusion.

4 The proposed protocol

GACRP uses a genetic algorithm with improved selection, crossover and mutation operations to find the optimal routing paths based on the selected CHs, which consists of three phases: clusters formation, routing paths finding, clusters maintenance. Next, they are successively introduced in detail.

4.1 Clusters formation

In order to minimize the energy consumption, it is necessary to determine the optimal number of clusters and find the appropriate CH of each cluster.

(1) the optimal number of clusters

For a circular network, the energy consumption of the CH E_{ch} in the last annulus differs from that in the other annuluses without data forwarding, which can be expressed as

$$E_{ch} = l \times E_{elec} \times (N_n - 1) + l \times E_{da} \times (N_n - 1) + (l \times E_{elec} + l \times \epsilon_{fs} \times d_{ch}^2) N_n \quad (4)$$

Where l is the length of data, N_n is the number of the cluster, n is the number of annulus, d_{ch} is the distance to the next hop CH which is depicted in Figure 1. $A(x_n, y_n)$, $B(x_{n-1}, y_{n-1})$ and C are CHs in the annuluses n and $n-1$, then $d_{ch} < d_0$. Moreover, there is $d_{ch} < r_c$ (radius of the cluster) for proper data transmission. From Figure1, it can be seen that the minimum d_{ch} is $\frac{R}{n}$ when the line of BC is perpendicular to the tangent z . So there is

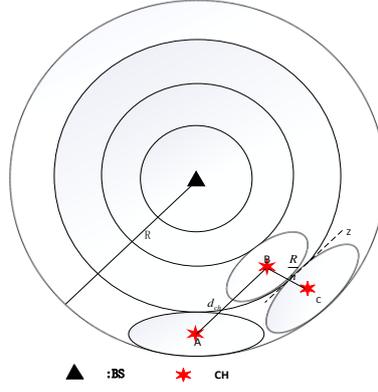


Fig.1 The distance to the next hop CH

$$\frac{R}{n} \leq d_{ch} < \min(r_c, d_0) \quad (5)$$

At the same time, the energy consumption of the members E_{cm} can be expressed as

$$E_{cm} = (l \times E_{elec} + l \times \varepsilon_{fs} \times d_{cc}^2)(N_n - 1) \quad (6)$$

where d_{cc} is the distance between member nodes and CH which can be denoted by the expectation of its square

$$E(d_{cc}^2) = \int_0^{2\pi} \int_0^{d_c} \rho \times r^3 dr d\theta = \frac{d_c^4 N}{2R^2} \quad (7)$$

where d_c is the maximum d_{cc} , which is depicted in Figure 2.

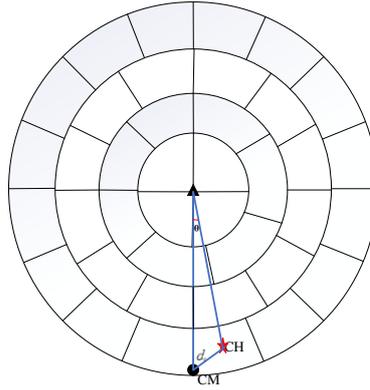


Fig. 2 Distance between a CM and its CH

Then d_c can be found according to cosine theorem

$$d_c^2 = R^2 + \left(R - \frac{R}{2n}\right)^2 - 2 \times R \times \left(R - \frac{R}{2n}\right) \times \cos\theta = (1 - \cos\theta) \left(2R^2 - \frac{R^2}{n}\right) + \frac{R^2}{4n^2} \quad (8)$$

where $\theta = \frac{\pi}{m_n}$ is the corresponding center angle, m_n is the optimal number of clusters. Therefore, the total energy consumption of the annulus can be expressed as

$$\begin{aligned} E_{total} &= m_n \times (E_{ch} + E_{cm}) \\ &= m_n \times l [N_n (3E_{elec} + E_{da} + \varepsilon_{fs} \times d_{ch}^2 + \varepsilon_{fs} \times d_{cc}^2) - \varepsilon_{fs} \times d_{cc}^2 - 2E_{elec} - E_{da}] \end{aligned} \quad (9)$$

Taking the derivative of Eq. (9) with respect to m_n , the optimal number of clusters can be attained:

$$m_n = \frac{-(\sqrt[3]{Y_1} + \sqrt[3]{Y_2})}{3} \quad (10)$$

$$Y_1 = \frac{-27B - 3\sqrt{81B^2 + 12A^2}}{2} \quad Y_2 =$$

$$\frac{-27B + 3\sqrt{81B^2 + 12A^2}}{2} \quad \text{and}$$

$$A = \frac{8n^2\pi^2 R^2 \varepsilon_{fs} N(1-2n)}{8n^3(2E_{elec} + E_{da}) - (12n^2 - 4n + 1)(1-2n)\varepsilon_{fs} N} \quad B = \frac{16n\pi^3 R^4 \rho \varepsilon_{fs} N(1-2n)}{8n^3(2E_{elec} + E_{da}) - (12n^2 - 4n + 1)(1-2n)\varepsilon_{fs} N} .$$

Similarly, the optimal number of clusters in the other annuluses can be obtained. Without loss of generality, for annulus i , the total energy consumption is

$$E_{TOTAL} = m_i \times (E_{ch} + E_{cm}) + (l \times E_{elec} + l \times \varepsilon_{fs} \times d_{ch}^2) (\sum_{j=i+1}^n m_j) \quad (11)$$

The second part of Eq. (11) represents the energy consumed to receive and relay the data from the CHs in annulus $i+1$ to n . Accordingly, the optimal number of clusters in annulus i is

$$m_i = \sqrt[3]{\frac{\varepsilon_{fs} \pi^3 \rho N R^4 (2i-1)(i-2i^2)}{4n^6(2lE_{elec} + lE_{da})}} \quad (12)$$

where ρ is the node density. Afterwards, each annulus is equally divided into sectors according to its optimal number of clusters, each sector forms a cluster, and the best node in this cluster will be selected as CH.

(2) Selecting the cluster heads

Similar to [5,6], a node in each cluster becomes CH when its weight is the maximum which is given as follows.

$$P_i = \frac{E_{residual_i}}{\sum_{j \in N_i} L_j} * \frac{E_{residual_i}}{E_{initial}} * \frac{\sum_{j \in N_i} d_{jBS}}{d_{iBS}} \quad (13)$$

Where $E_{residual_i}$ is the residual energy of node i , and $E_{initial}$ is the initial energy of each node. N_i denotes the set of neighbors for node i , and d_{iBS} denotes the distance between node i and the BS. It can be seen from Eq. (13) that the nodes with more residual energy, more uniform load and closer to the center of neighbors are more likely to be selected as CHs. Once the CHs are selected, their IDs and residual energy are sent to the BS for global routing paths finding, and a TDMA scheme like in [4,10,13] is used for intra-cluster communication.

4.2 Routing paths finding

An improved genetic algorithm is used to find the optimal routing path for each CH because the traditional genetic algorithm has some drawbacks such as premature convergence and local optimum [27]. Moreover, invalid individuals may be generated in traditional genetic algorithm due to its random operations of selection, crossover and mutation. So in GACRP, a constraint condition is provided for producing appropriate genes to avoid invalid individuals as well as improve the convergence speed. The concrete realization of finding routing paths is elaborated as follows.

(1) Constructing fitness function

Fitness function is used to assess the quality of the individuals which represent the possible solutions for routing paths. To maximize the network lifetime, it is necessary to decrease the CHs' amount of energy consumption as much as possible. So the residual energy of all CHs is considered as a factor for the fitness function, which is given by

$$E_{CHres} = \sum_{j=1}^{m_n} E_{residual_{h_{nj}}} + \sum_{i=1}^{n-1} \sum_j^{m_i} E_{residual_{h_{ij}}} \quad (14)$$

where $E_{residual_{h_{ij}}}$ denotes the residual energy of the j^{th} CH of the i^{th} annulus. Moreover, E_{CHres} is normalized as

$$E_{CHres} = \frac{E_{CHres} - E_{CHres_min}}{E_{CHres_max} - E_{CHres_min}} \quad (15)$$

where $E_{CHres_min}, E_{CHres_max}$ are the minimum and maximum of E_{CHres} respectively. In addition, balance of loads L_{CHs} for CHs also has great influence on energy efficiency, which is used as the other factor for the fitness function. L_{CHs} denotes load balance of the CHs, which is given by

$$L_{CHs} = \sqrt{\frac{\sum_{i=1}^{n_{ch}} \left(\frac{E_{residual_{h_i}}}{L_{h_i}} - \frac{\sum_{i=1}^{n_{ch}} E_{residual_{h_i}}}{n_{ch}} \right)^2}{n_{ch}}} \quad (16)$$

where h_i means the i^{th} CH, n_{ch} denotes the number of CHs, E_{h_i} denotes the energy consumption of h_i , L_{h_i} is the load of CH h_i . Therefore, the fitness function in GACRP is expressed as follows:

$$Fitness = \frac{1}{1+L_{CHs}} + E_{CHres} \quad (17)$$

It can be seen from Eq. (17) that the higher the value of the fitness function, the better the quality of the individual, and then the more likely it is passed on to the next generation.

(2) Initializing the population

In GACRP, real number encoding is used to represent the chromosomes of the population. A chromosome means an individual consisting of genes denoted by the IDs of CHs, and the ID of the BS equals $n_{ch}+1$. A specific gene of the chromosome indicates the next-hop CH of the corresponding CH with an example illustrated in Figure 3.

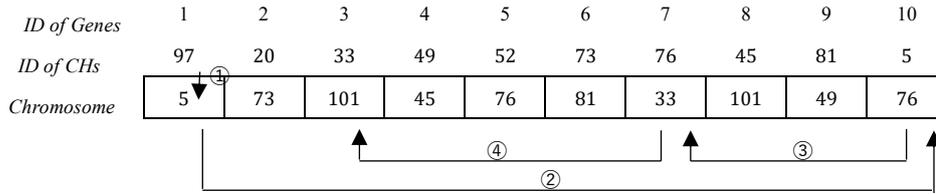


Fig. 3 Valid chromosome for GACRP

As shown in Figure 3, supposing there is 10 CHs selected from the network with 100 nodes, and their IDs are 5, 20, 33, 45, 49, 52, 73, 76, 81, 97 respectively. From the chromosome, it can be seen that the routing paths for CH 97 is $97 \rightarrow 5 \rightarrow 76 \rightarrow 33 \rightarrow 101$ (the BS). The genes are randomly produced like in traditional genetic algorithm, but a constraint condition $g_i \in CH_{h_i}$ (CH_{h_i} is the candidate next-hop CHs for h_i , which are located in the range of communication of h_i). And i is the number of genes, $i \in [1, 10]$ in Figure 3) is attached to gene g_i in order to avoid invalid individuals such as in Figure 4.

<i>ID of Genes</i>	1	2	3	4	5	6	7	8	9	10
<i>ID of CHs</i>	97	20	33	49	52	73	76	45	81	5
<i>Valid Chromosome</i>	5	73	101	45	76	81	33	101	49	76
	↓ $CH_{h_1} = \{h_{10}(5), h_8(45), h_9(81)\}$					↓ $CH_{h_6} = \{h_9(81), BS(101)\}$				
<i>Invalid Chromosome</i>	49	73	101	45	76	49	33	101	49	76

Fig. 4 Invalid chromosome for GACRP

In the same way, the other valid chromosomes are produced to obtain the initial population.

(3) Producing the next generation population

The value of the fitness function for each chromosome in the initial population is calculated, which is arranged in descending order. The higher the value of the fitness function, the closer individual is to the optimal solution. The elitist selection is used for selection operation, which selects the optimal individuals directly passed on to the next generation population. For the other chromosomes, each one determines whether its fitness

function value is less than that of a randomly generated valid individual. If less than, it is selected for crossover operation, otherwise, the random one is selected for crossover operation so as to accelerate convergence as well as ensure the diversity of the population.

One-point crossover is used to produce new offspring based on the selected individuals. Because the parents are valid chromosomes, so their two children must be still valid. Then the fitness function value of each child is computed to compare with its parent. If its value is less than that of its parent, it is selected for mutation operation. Or else, a randomly generated individual is used to determine whether its fitness function value is less than that of the parent. If it is, the random individual is selected for mutation operation, otherwise, the father is selected. In this way, the convergence speed is further accelerated.

Bit mutation is used for mutation operation, in which a random mutation point is selected to change the corresponding gene so as to produce a new individual. Of course, the new individual must be valid whose mutated gene is satisfied with the constraint condition. Similarly, its fitness function value is calculated to determine whether it is superior to its parent, and the better one is selected to the next generation. Figure 5 shows an example of the mutation operation.

<i>ID of Genes</i>	1	2	3	4	5	6	7	8	9	10
<i>ID of CHs</i>	97	20	33	49	52	73	76	45	81	5
<i>Parent</i>	5	73	101	45	76	81	33	101	49	76
	↓ <i>Mutation point</i>									
<i>Child</i>	45	73	101	45	76	81	33	101	49	76

Fig. 5 Bit mutation for GACRP

Combined these new individuals with the elitist ones will produce the next generation population.

(4) Finding the optimal routing paths

One of the following termination conditions is satisfied, GACRP finds the optimal routing paths. One is the preset iteration number, the other is the deviation degree of the fitness function values which is expressed as follows:

$$\left| \frac{\sum_{i=1}^k Fitness_i}{k} - Fitness_{max} \right| \leq \epsilon \tag{11}$$

where $Fitness_i$ denotes the fitness function value of individual i , and $Fitness_{max}$ denotes the maximum fitness function value, ϵ is a small positive number which equals 10^{-5} in this paper like [27]. The individual with minimum fitness function value is selected from the population, which gives the optimal routing path for each CH. The flow diagram of finding the optimal paths is depicted in Figure 6.

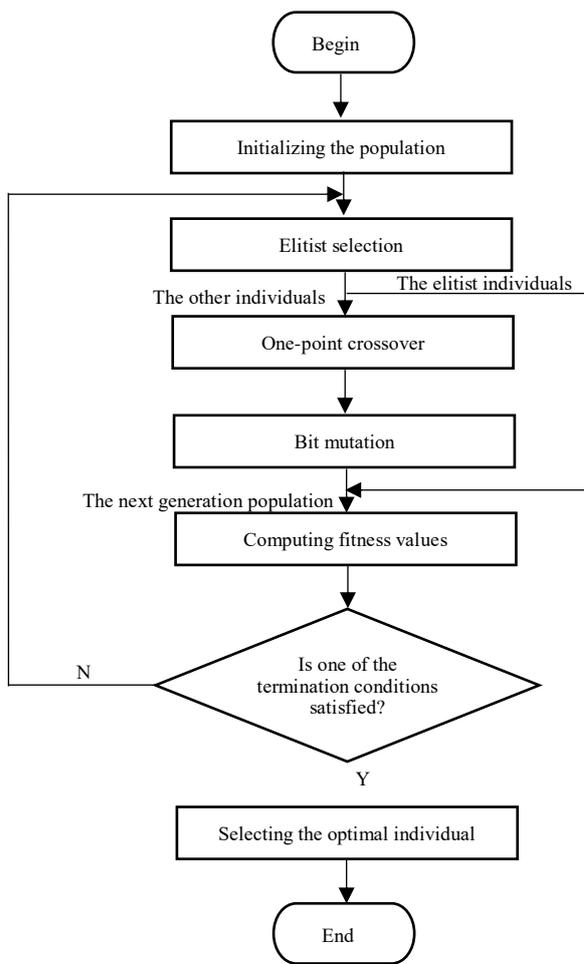




Fig. 6 The flow diagram of finding the optimal routing paths

4.3 Clusters maintenance

Generally, fixed round time [4,10,13] is used for CHs rotation during the entire network operation so as to reduce the energy consumption. However, frequent clustering may cause more energy consumption for fixed round based approaches. Therefore, in GACRP, a new adaptive round time is proposed to save energy consumption due to frequent CHs rotation and improve the throughput of the network. Here, the load balancing and the energy balancing of the network are both considered, which are represented as α and β .

$$T_{newround} = 2 * T_{round} * \alpha * \beta \quad (12)$$

Where:

- T_{round} is the traditional round time
- α is the load balancing factor which is given by

$$\alpha = \frac{L_{CHS} - L_{CHSmin}}{L_{CHSmax} - L_{CHSmin}}$$

L_{CHSmin} and L_{CHSmax} are the minimum and maximum of L_{CHS} .

- β is the energy balancing factor which is given by

$$\beta = \frac{E_{HRES} - E_{HRESmin}}{E_{HRESmax} - E_{HRESmin}}$$

where

$$E_{HRES} = \sqrt{\frac{\sum_{i=1}^{n'_{ch}} (E_{residual_i} - \frac{\sum_{i=1}^{n'_{ch}} E_{residual_i}}{n'_{ch}})^2}{n'_{ch}}}$$

n'_{ch} denotes the number of alive CHs in the network. Obviously, no extra overhead is produced for the residual energy and state of the nodes is usually attached by the nodes in the data packets delivered to the BS. At the beginning of each round, the BS uses the improved genetic algorithm to obtain the optimal routing paths according to the received CHs, and then broadcasts them to the network together with the calculated round time. Each node communicates with each other based on the received information.

5 Simulation and results

In this section, simulations are conducted through MATLAB to verify the performance of GACRP compared with the up-to-date correlative algorithms LEACH [4], AEBDC [10], TSTCS [13] and OMPFM [24]. In the simulations, N nodes are scattered randomly in the circular networks with radius 100m and 200m, and the BS is located at the center. The detail parameter settings are shown in Table 1.

Table 1 Parameter settings

Parameters	Values
Initial energy of node	1J
E_{elec}	50nJ/bit
ϵ_{fs}	10pJ/bit/m ²
ϵ_{mp}	0.0013pJ/bit/m ⁴
E_{pDb}	5nj/bit
Packet size l	4000 bits
Message size	100 bits
Maximum communication range of nodes/ d_{max}	50m
Network radius R	100m, 200m

Crossover rate	0.85
Mutation rate	0.15
Population number	100

The total energy consumption of all nodes is firstly tested to show the performance of energy efficiency of GACRP, and the results are illustrated in Figure 7.

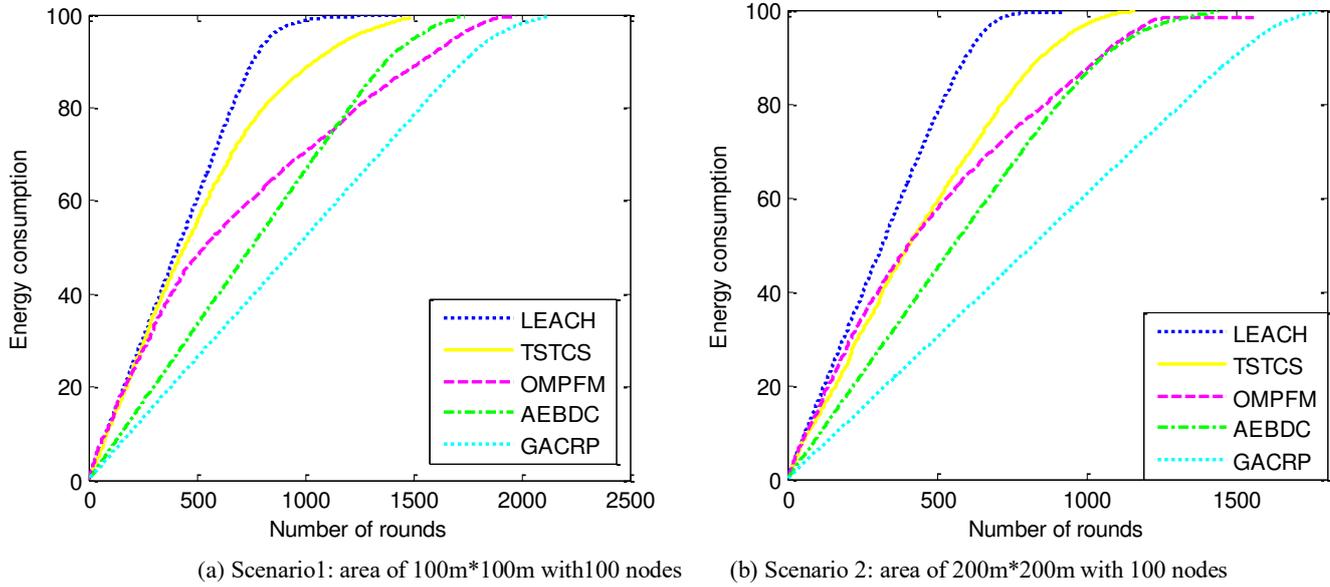


Fig.7 Comparison of energy efficiency

As can be seen from Figure 7, LEACH is the first to consume the energy of all nodes because of its single-hop communication, random CHs selection without considering their residual energy, thus its performance is the worst. TSTCS and AEBDC divide the network into rings, and the CHs in an outer ring forward data to the CHs in its adjacent inner ring, follow this till to the BS in the end, so their energy consumption is lower than that of LEACH. OMPFM can find the optimal routing paths for CHs by using genetic algorithm compared with TSTCS and AEBDC, its energy consumption is less than that of TSTCS and AEBDC, on the whole. However, OMPFM selects CHs using different threshold functions in three stages, which directly affects the distribution of clusters and routing paths finding, resulting in energy consumption is faster than TSTCS and AEBDC sometimes. Unlike random clustering in LEACH, TSTCS, AEBDC and OMPFM, GACRP forms clusters according to the calculated optimal cluster number. Moreover, an improved genetic algorithm considering energy and load balance is used to find the optimal routing paths, so its energy consumption is the lowest whether in scenario 1 or 2. As a result, the total energy consumption of GACRP is 24.53%, 21.84%, 1.68% and 2.69% lower than those of LEACH, TSTCS, AEBDC and OMPFM in scenario 1, while 43.96%, 29.31%, 12.72% and 5.94% in scenario 2.

And then, the standard deviation of CHs' residual energy in two scenarios is tested to verify the performance of energy balance for GACRP, and the results are shown in Figure 8.

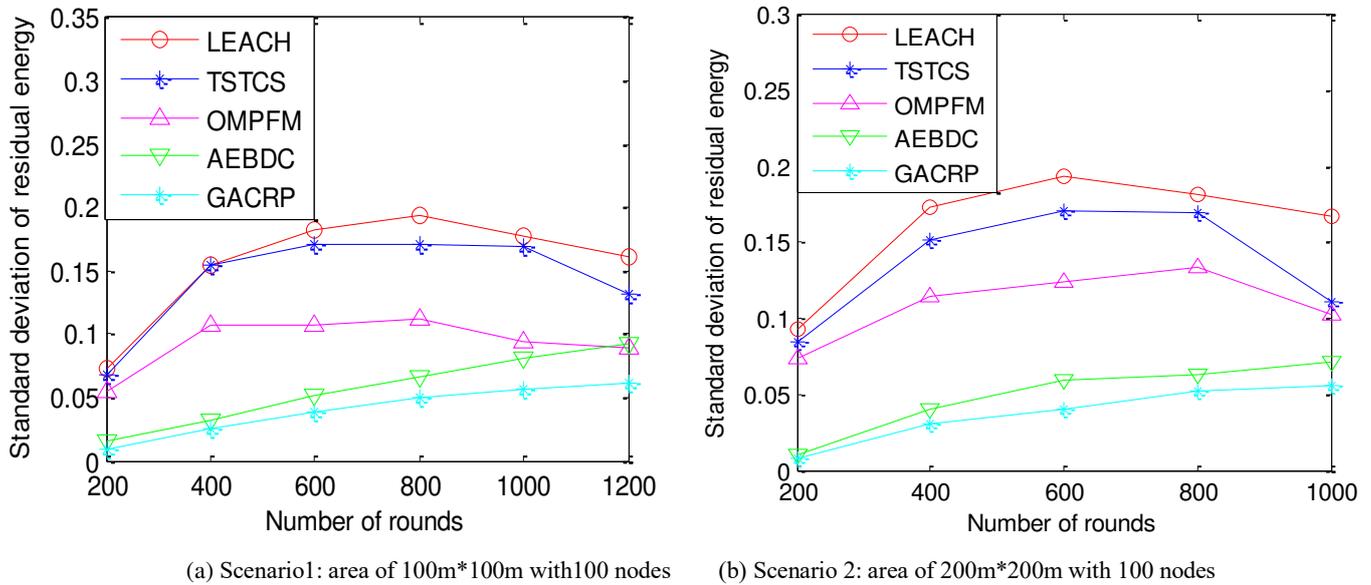
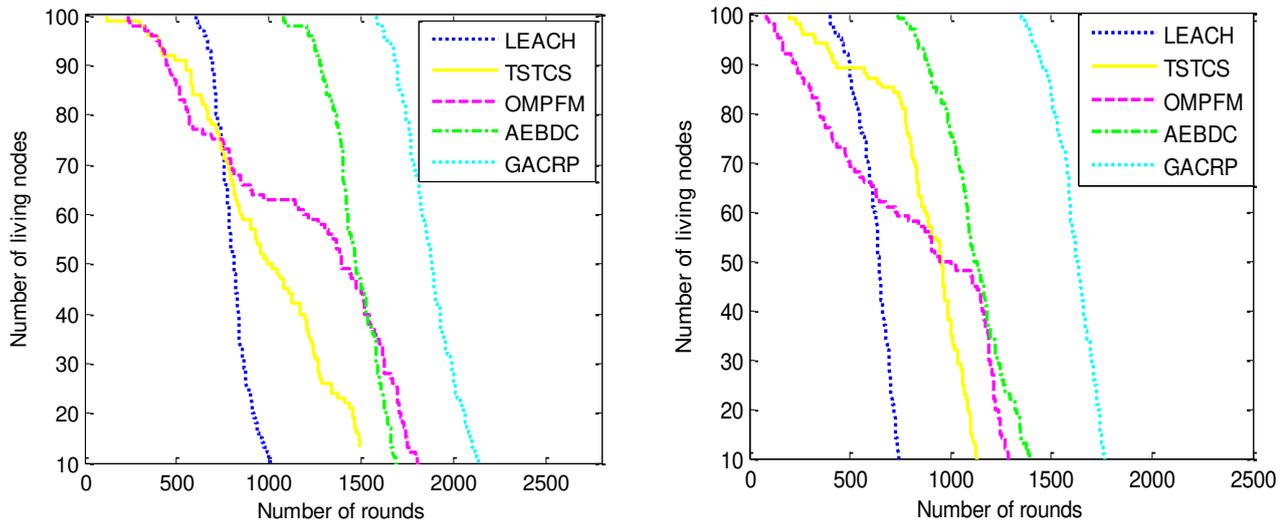


Fig.8 Comparison of standard deviation of CHs residual energy

It can be seen from Figure 8 that GACRP has the best performance of energy balance, while LEACH has the worst. LEACH randomly selects CHs and transfers data to the BS in single-hop mode, resulting in quite different energy consumption between CHs close to the BS and those far from the BS. For TSTCS, the CHs in outer ring transmit data to the adjacent CHs in inner ring, so the energy consumption of CHs in inner ring is higher than that in outer ring because of data forwarding. OMPFM and GACRP use genetic algorithm to find the optimal routing paths for CHs, especially, CHs in outer ring transmit data to CHs in inner ring so as to balance the energy consumption in AEBDC. Accordingly, the residual energy deviation of CHs in TSTCS is higher than that of OMPFM, AEBDC and GACRP. Moreover, in GACRP, the energy consumption and load balance of CHs are fully considered in fitness function construction, which reduces the standard deviation of CHs' residual energy. Compared with LEACH, TSTCS, OMPFM and AEBDC, the standard deviation of residual energy of GACRP is decreased by 74.35%, 72.05%, 57.08%, 28.8% in scenario 1, and 76.99%, 72.87%, 66.06%, 23.72% in scenario 2, respectively.

Next, the network lifetime is tested to evaluate the survivability of GACRP, and the results are shown in Figure 9, Table 2 and Table 3.

It is obvious that LEACH has the worst performance, its FND (first node die) appears at round 603 in scenario 1, and its LND (last node die) is at round 1445. In scenario 2, FND and LND occur at round 400 and 1022 respectively. LND of OMPFM at round 1950, 1482 and TSTCS at round 1589, 1205 are larger than that of LEACH in both scenarios, however, their FND at round 241, 89 and 121, 201 are smaller than that of LEACH, because ring by ring communication in TSTCS and clustering based on piecewise threshold function in OMPFM result in uneven energy consumption. Moreover, AEBDC uses a vice CH to share the forwarding task of the primary CH, which can balance the energy consumption, its FND and LND are at round 1079, 739 and 1734, 1436 in scenario 1 and 2, respectively, so it is superior to LEACH, TSTCS and OMPFM. GACRP forms more uniform clusters than LEACH, TSTCS, OMPFM and AEBDC by computing the optimal cluster number in each annulus, what's more, the optimal routing paths for CHs can be obtained in GACRP by an improved genetic algorithm with a novel fitness function considering energy and load balance, therefore, GACRP has the longest lifetime with FND and LND at round 1584, 1355 and 2234, 1869 in scenario 1 and 2. In short, the network lifetime of GACRP is increased by 54.60%, 40.59%, 14.56%, 28.84% in scenario 1, and by 82.88%, 55.10%, 26.11%, 30.15% in scenario 2, compared to LEACH, TSTCS, OMPFM and AEBDC.



(a) Scenario 1: area of 100m*100m with 100 nodes (b) Scenario 2: area of 200m*200m with 100 nodes

Fig.9 Comparison of the number of living nodes

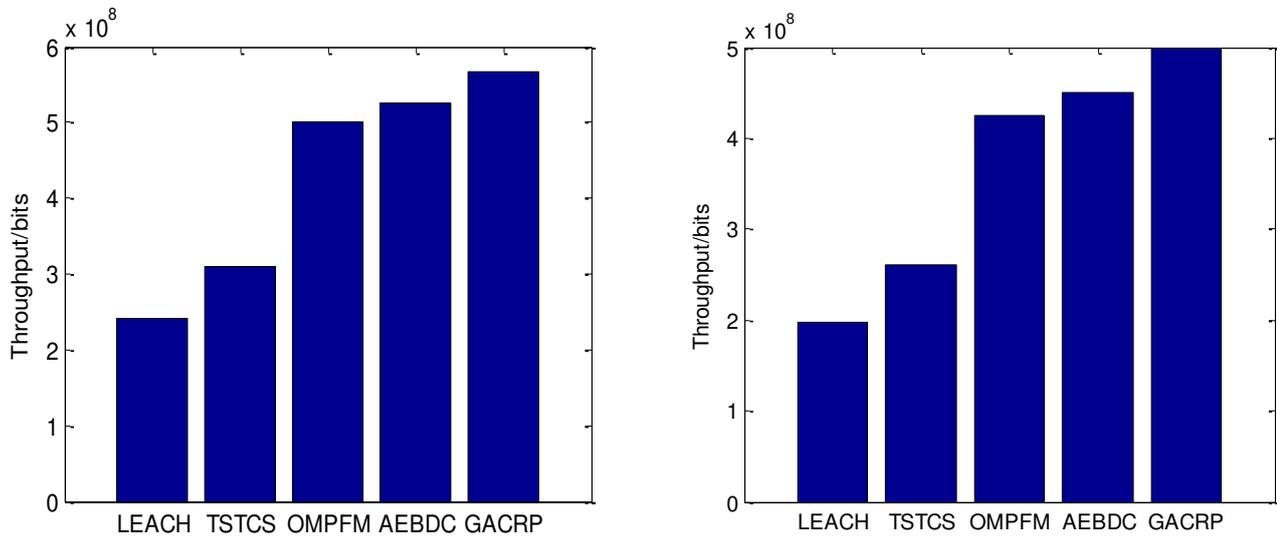
Table 2 The network lifetime in Scenario 1 with area of 100m*100m

Items \ Protocols	LEACH	TSTCS	OMPFM	AEBDC	GACRP
FND	603	121	241	1079	1584
HND	811	986	1390	1468	1879
LND	1445	1589	1950	1734	2234

Table 3 The network lifetime in Scenario 2 with area of 200m*200m

Items \ Protocols	LEACH	TSTCS	OMPFM	AEBDC	GACRP
FND	400	201	89	739	1355
HND	643	954	949	1119	1625
LND	1022	1205	1482	1436	1869

The network throughput is denoted by the effective received data packets of the BS, which is an important indicator to measure the network quality of service and a direct reflection of CHs' load balance, so it is tested to verify the QoS of GACRP and the results are depicted in Figure 10.

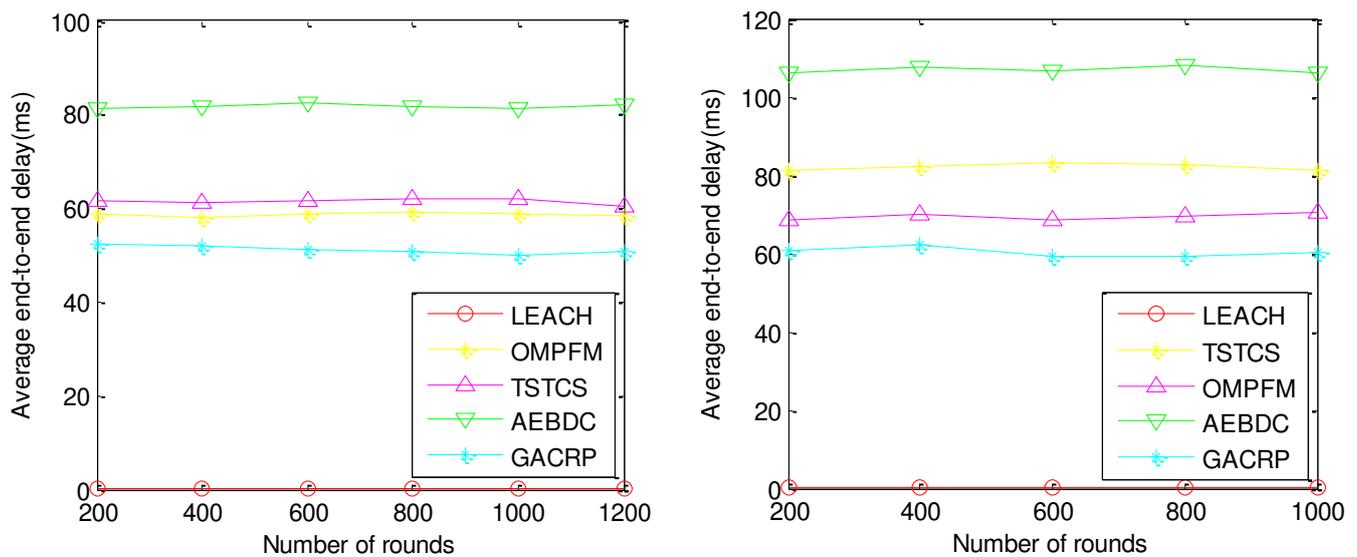


(a) Scenario 1: area of 100m*100m with 100 nodes (b) Scenario 2: area of 200m*200m with 100 nodes

Fig.10 Comparison of network throughput

As can be seen from Figure 10 (a) and (b), the network throughput of LEACH is the least due to its shortest lifetime. In TSTCS, the CHs close to the BS consume too much energy on data forwarding, resulting in their premature death. Consequently, a large number of data in the outer rings is unable to be transmitted to the BS. Compared with TSTCS, AEBDC shares the task of data forwarding by using the vice CHs in clusters, so its performance is better than that of TSTCS. In GACRP, the optimal routing paths are selected to transmit more data to the BS based on the best number of clusters. In Scenario 1, the network throughput of GACRP is 57.6%, 45.23%, 11.68% and 7.09% higher than LEACH, TSTCS, OMPFM and AEBDC. In Scenario 2, the network throughput of GACRP is increased by 60.49%, 47.72%, 14.69% and 9.62% compared with LEACH, TSTCS, OMPFM and AEBDC.

Average end-to-end delay denoted by the average time of CHs taking to send data to the BS is an important metric to evaluate the real-time performance and fast data forwarding capability. So average end-to-end delay is tested under different packet sending rate, and the results are illustrated in Figure 11.



(a) Scenario 1: area of 100m*100m with 100 nodes (b) Scenario 2: area of 200m*200m with 100 nodes

Fig.11 Comparison of average end-to-end delay

It can be seen from Figure 11 that the average end-to-end delay of LEACH is minimal due to its CHs' direct communication with the BS. In AEBDC, the CHs need to find the optimal vice CHs before sending data, which leads to the highest average end-to-end delay. Unlike ring-by-ring data forwarding in TSTCS, the CHs use the optimal routing paths determined by genetic algorithm to transfer data in OMPFM and GACRP, so their average end-to-end delay is lower than that of TSTCS. Differing from the random clustering in TSTCS, uniform clusters are formed in GACRP by dividing the network into equal annulus-sector based on the optimal cluster number, which makes the average end-to-end delay of GACRP is lower than that of OMPFM. As a result, the average end-to-end delay of GACRP outperforms OMPFM by 12.74%, 12.96%, TSTCS by 16.79%, 26.54% and AEBDC by 37.37%, 43.6% in Scenario 1 and 2, respectively.

6 Conclusion

In this paper, an annulus-sector clustering routing protocol GACRP is proposed to minimize the network energy consumption and balance the network load by using an improved genetic algorithm. In GACRP, the optimal cluster number of each annulus is used for annulus-sector division, which minimizes the energy consumption of each annulus. And the best nodes in the annulus sectors are selected for data aggregation, transmission and forwarding, which balances the intra-cluster loads and energy consumption. Moreover, genetic algorithm with a novel fitness function considering energy and load balance is used to find the optimal routing paths for CHs, which balances the inter-cluster loads and energy consumption. In addition, an adaptive round time is utilized to maintain the clusters, which further reduces the network energy consumption. Simulation experiments are conducted to verify the performance of GACRP compared with several existing relevant protocols such as LEACH, AEBDC, TSTCS and OMPFM. The results show that GACRP can not only effectively alleviate the hot spot problem but also outperform these protocols in terms of energy efficiency, average end-to-end delay, network throughput and network lifetime.

Funding: "Thirteenth Five-Year" Science and Technology Project of Education Department of Jilin Province (grant no. JJKH20181013KJ & JJK H20181166KJ). Province Development and Reform Commission Project (grant no. 2019C054-4).

Conflicts of Interest: The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Availability of data and material: This article has no data and material availability.

Code availability: Custom code.

Author Contributions: Conceptualization, W.C.H, L.X.L and H.Y.J; methodology, W.C.H and H.Y.J; writing—original draft preparation, H.Y.J; writing—review and editing, W.C.H and H.Y.J; supervision, W.S.S and H.H.S; All authors have read and agreed to the published version of the manuscript.

References

1. Mohammed S B, Raoudha S, Yessine H K, et al. Wireless sensor network design methodologies: a survey. *Journal of Sensor*, 2020, 2020(1):1-13.
2. Guleria K, Verma A K. Comprehensive review for energy efficient hierarchical routing protocols on wireless sensor networks. *Wireless Networks*, 2019, 25(2019): 1159-1183.
3. Fanian F, Rafsanjani M K. Cluster-based routing protocols in wireless sensor networks: a survey based on methodology. *Journal of Network and Computer Applications*, 2019, 2019(142): 111-142.
4. Heinzelman W R, Chandrakasan A, Balakrishnam H. Energy-efficient communication protocol for wireless microsensor networks[C] // *Proceedings of the 33rd Annual Hawaii International Conference on System Sciences*. Piscataway, NJ: IEEE, 2000: 3eneti005-3014.
5. Robinson Y H, Julie E G, Kumar R, et al. Probability-based cluster head selection and fuzzy multipath routing for prolonging lifetime of wireless sensor networks. *Peer-to-Peer Networking and Application*, 2019, 2019(12): 1061-1075.
6. K. Nadjet, B. M. Louiza and A. Djamil. Clustering with Load Balancing-Based Routing Protocol for Wireless Sensor Networks. *Wireless Pers. Commun.*, 2018, 109(3): 2155-2175.

7. Nouredine M, Zakaria H A, Abdelbaki E B EA. ECRP: an energy-aware cluster-based routing protocol for wireless sensor networks. *Wireless Networks*, 2020, 2020(26): 2915-2928.
8. Wang J, Gao Y, Liu W, Sangaiah A K, Kim H J. An improved routing schema with special clustering using PSO algorithm for heterogeneous wireless sensor network. *Sensors*, 2019, 2019(19): 1-17.
9. Kiran W S, Smys S, Bindhu V. Enhancement of network lifetime using fuzzy clustering and multidirectional routing for wireless sensor networks. *Soft Computing*, 2020, 2020(24): 11805-11818.
10. Chao Sha, Qin Liu, Song Si-yi, Wang Ru-chuan. A type of annulus-based energy balanced data collection method in wireless rechargeable sensor networks. *Sensor*, 2018, 2018(18): 1-29.
11. Huang J H, Ruan D W, Meng W Q. An annulus sector grid aided energy-efficient multi-hop routing protocol for wireless sensor networks. *Computer Networks*, 2018, 147(2018): 38-48.
12. Karthika S, Velappa G, Priyanka S. Energy minimization in wireless sensor network by incorporating unequal clusters in multi-sector environment. *Cluster Computing*, 2017,
13. Naveen J, Alphonse P J A, Chinnasamy S. Track-sector-tree clustering scheme for dense wireless sensor networks. 2017,
14. Moon S H, Park S, Han S J. energy efficient data collection in sink-centric wireless sensor networks: a cluster-ring approach. *Computer Communications*, 2017, 101(2017):12-25.
15. Songyut P, Chakchai S I, Phet A, et al. An energy-efficient fuzzy-based scheme for unequal multihop clustering in wireless sensor networks. *Journal of Ambient Intelligence and Humanized Computing*, 2020,
16. Vijayalakshmi V, Senthilkumar A. USCDRP: unequal secure cluster-based distributed routing protocol for wireless sensor networks. *The Journal of Supercomputing*, 2020, 2020(76): 989-1004.
17. Zhao L, Qu S C, Yi Y F. A modified cluster-head selection algorithm in wireless sensor networks based on LEACH. *EURASIP Journal on Wireless Communication and Networking*, 2018, 2018(287): 1-8.
18. Singh S K, Kumar P, Singh J P. A survey on successors of LEACH protocol. *IEEE Access*, 2017, 2017(5): 4298-4328.
19. Cai X J, Sun Y Q, Cui Z H, et al. Optimal LEACH protocol with improved bat algorithm in wireless sensor networks. *KSII Transactions on Internet and Information System*, 2019, 13(5): 2469-2490.
20. Balaji S, Julie G, Robinson Y H. Development of fuzzy based energy efficient cluster routing protocol to increase the lifetime of wireless sensor networks. *Mobile Network Application*, 2019, 24(2019): 394-406.
21. Tarunpreet B, Simmi K, Shivani G, et al. A genetic algorithm based distance-aware routing protocol for wireless sensor networks. *Computers and Electrical Engineering*, 2016, 56(2016): 441-455.
22. Gupta, V., Pandey, R., 2016. An improved energy aware distributed unequal clustering protocol for heterogeneous wireless sensor networks. *An International Journal of Engineering Science and Technology*, 2016, 2016(19): 1050-1058.
23. Baranidharan B, Santhi B. DUCF: distributed load balancing unequal clustering in wireless sensor networks using fuzzy approach. *Applied Soft Computing*, 2016, 2016(40): 495-506.
24. Mohammed A S, Mohammed A, Tat-chee W, et al. Energy efficient multi-hop in wireless sensor networks using an enhanced genetic algorithm. *Information Science*, 2019, 500(2019): 259-273.
25. X. Min , Energy efficient clustering algorithm for maximizing lifetime of wireless sensor networks, *Int. J. Electron. Commun.* 64 (4) (2010) 289-298.
26. Arghavani M, Esmacili M, Mohseni F, Arghavani A. Optimal energy aware clustering in circular wireless sensor networks. *Ad Hoc Networks*, 2017, 2017(65): 91-98.
27. Cao Y N, Wu M Q. A Novel RPL Algorithm Based on Chaotic Genetic Algorithm. *Sensors*, 2018, 2018(18): 1-20.

Figures

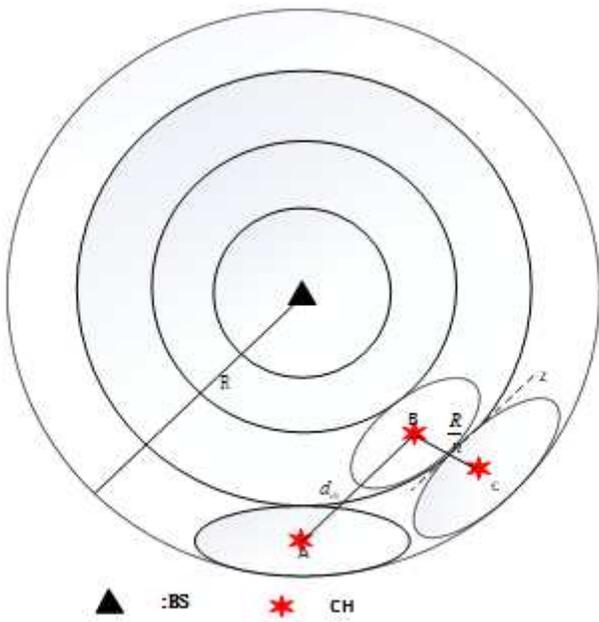


Figure 1

The distance to the next hop CH

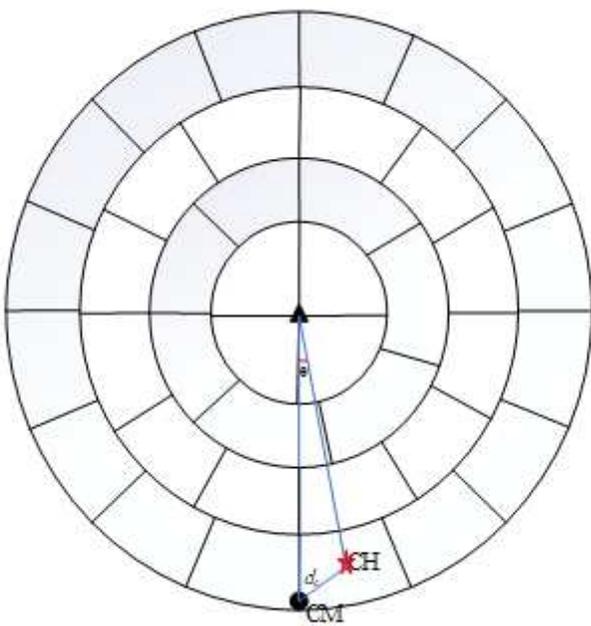


Figure 2

Distance between a CM and its CH

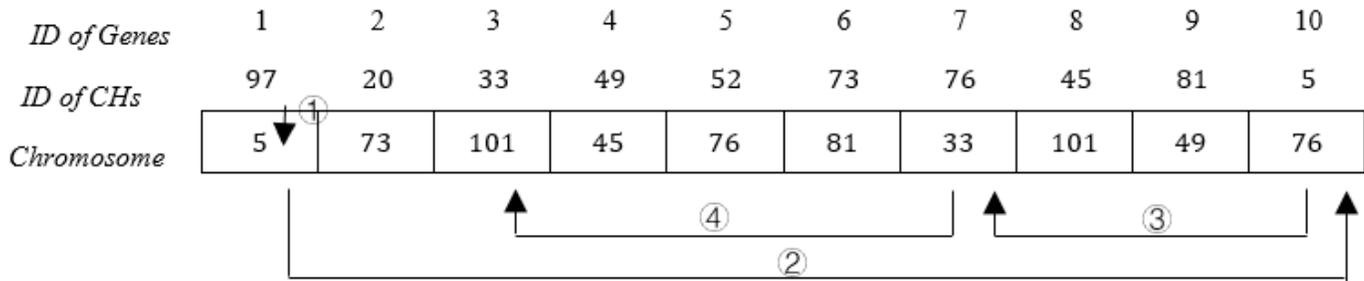


Figure 3

Valid chromosome for GACRP

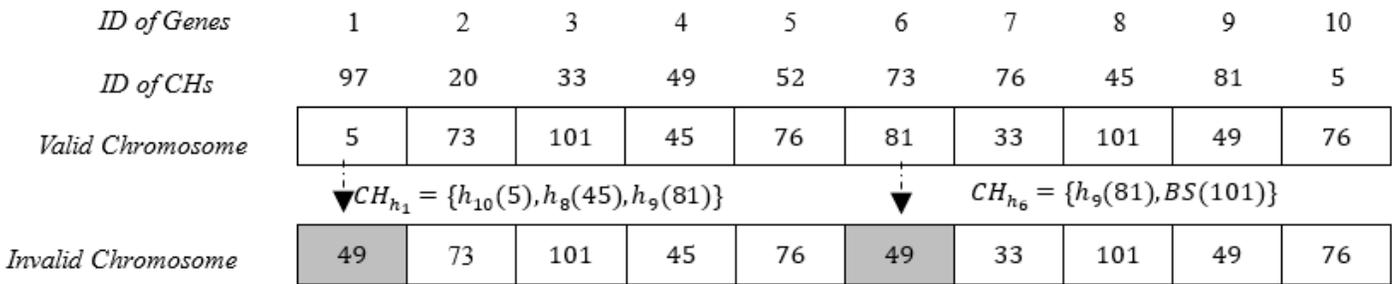


Figure 4

Invalid chromosome for GACRP

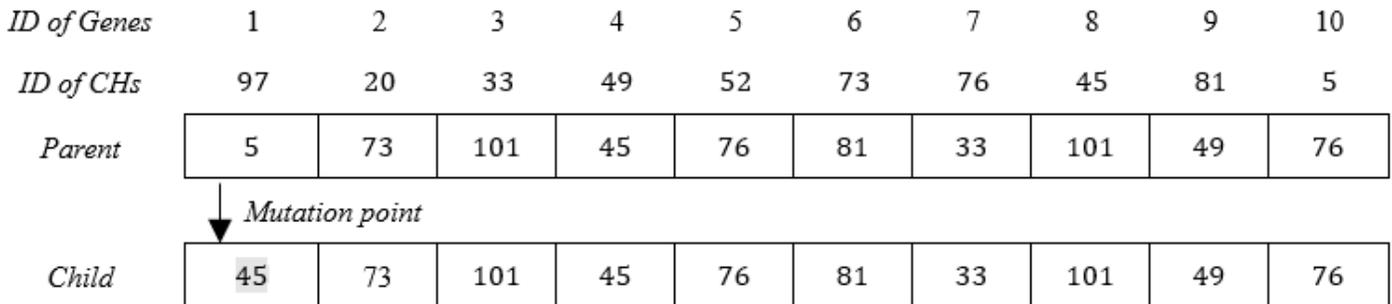


Figure 5

Bit mutation for GACRP

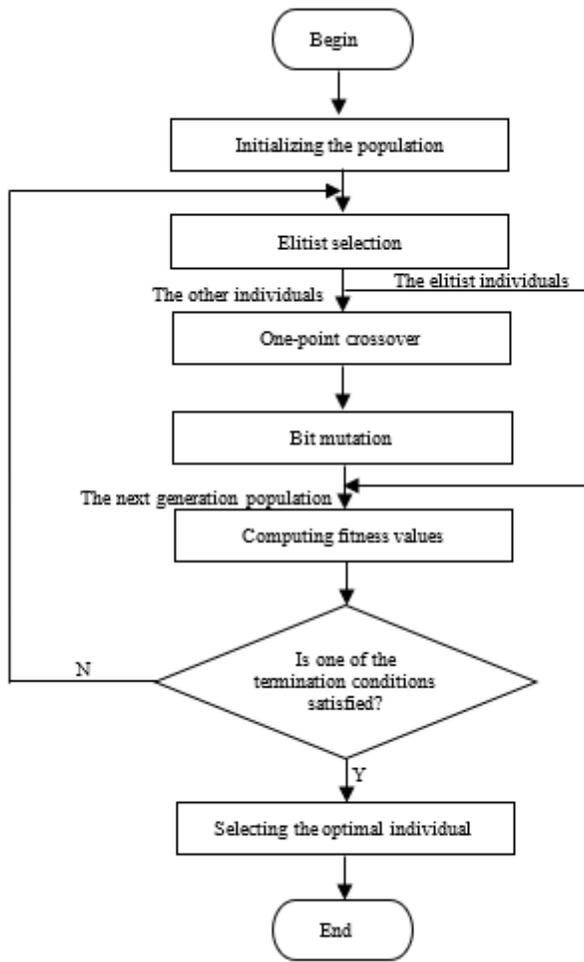


Figure 6

The flow diagram of finding the optimal routing paths

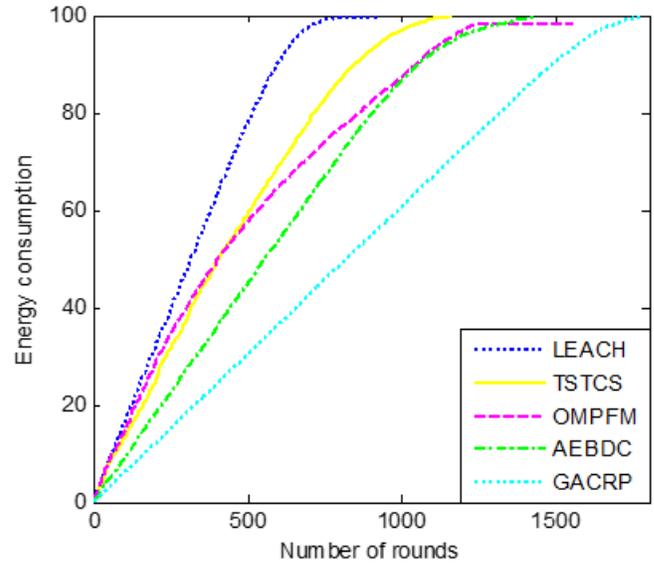
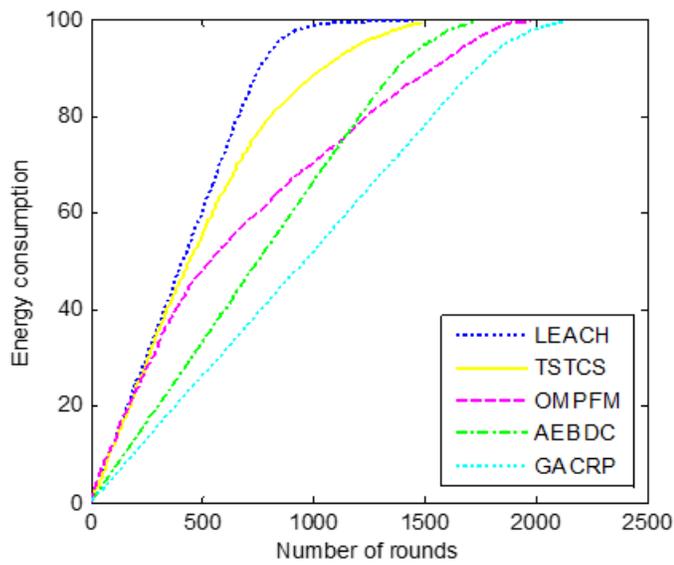


Figure 7

Comparison of energy efficiency. (a) Scenario1: area of 100m*100m with100 nodes (b) Scenario 2: area of 200m*200m with 100 nodes

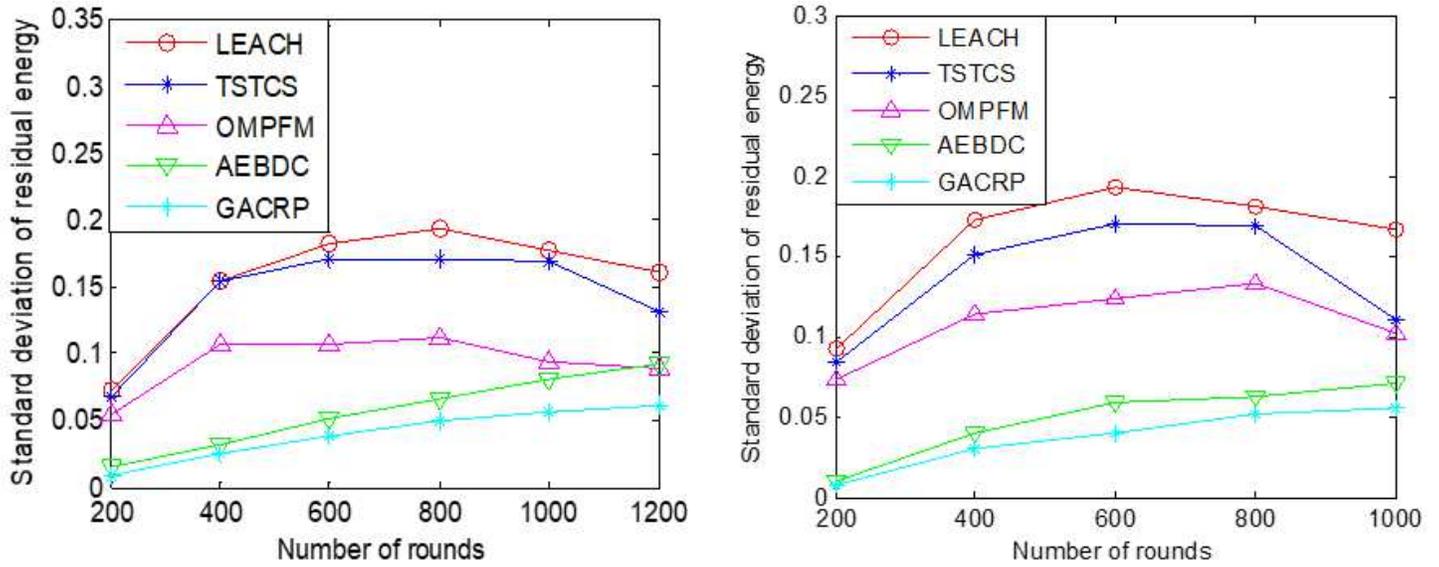


Figure 8

Comparison of standard deviation of CHs residual energy. (a) Scenario1: area of 100m*100m with100 nodes (b) Scenario 2: area of 200m*200m with 100 nodes

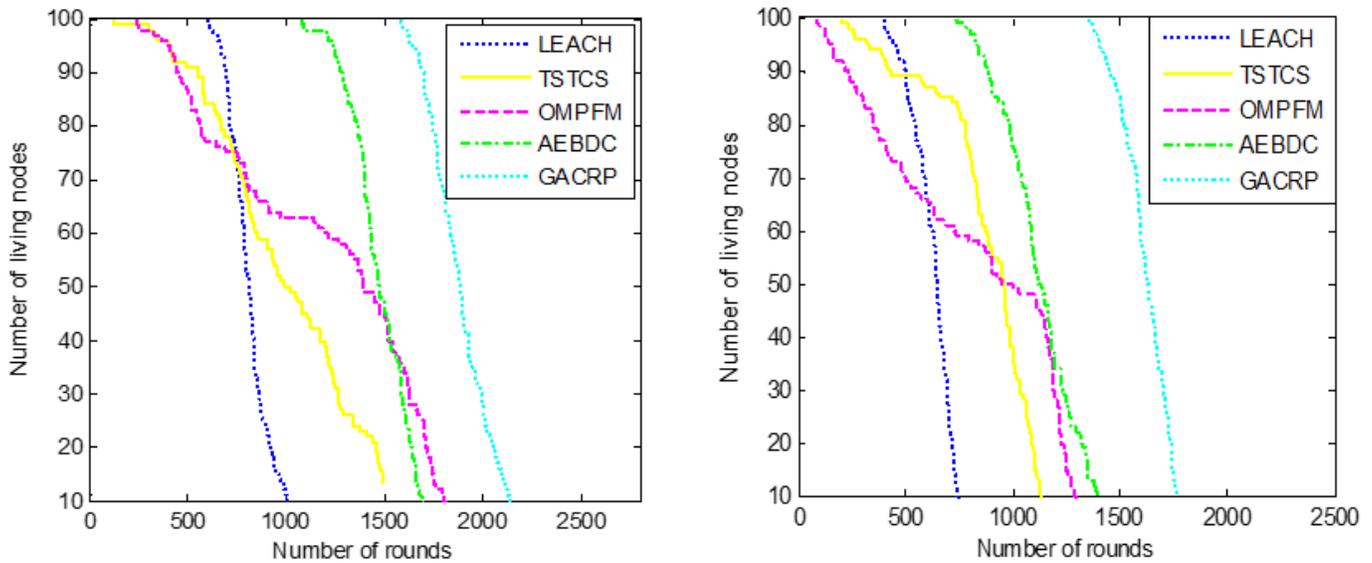


Figure 9

Comparison of the number of living nodes. (a) Scenario1: area of 100m*100m with100 nodes (b) Scenario 2: area of 200m*200m with 100 nodes

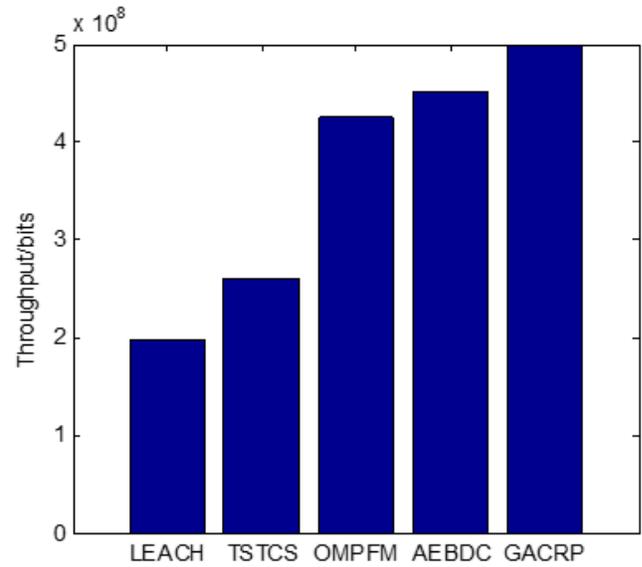
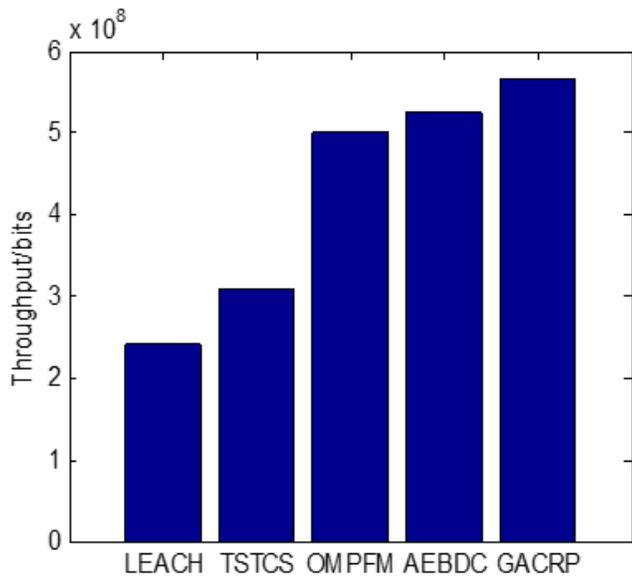


Figure 10

Comparison of network throughput. (a) Scenario1: area of 100m*100m with 100 nodes (b) Scenario 2: area of 200m*200m with 100 nodes

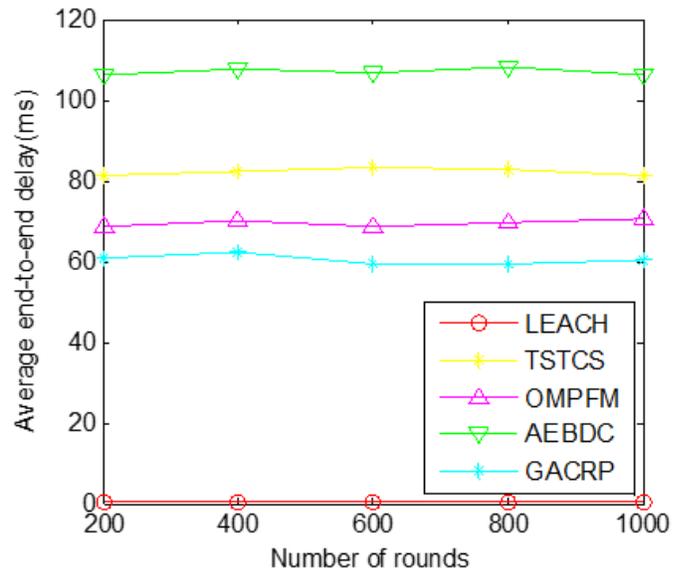
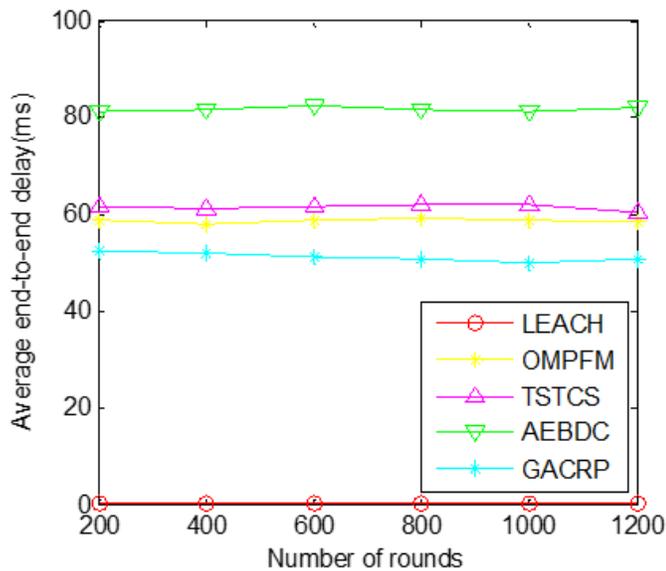


Figure 11

Comparison of average end-to-end delay. (a) Scenario1: area of 100m*100m with 100 nodes (b) Scenario 2: area of 200m*200m with 100 nodes