Evolutionary game–based trajectory design algorithm for mobile sink in wireless sensor networks

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Abstract
In wireless sensor networks, if sink node is stationary, the nodes close to sink will deplete energy faster than those in other areas. The unbalanced energy consumption among the nodes will lead to the energy hole problem, which shortens the network lifetime. To solve the problem, evolutionary game–based trajectory design algorithm for mobile sink in wireless sensor networks is proposed in this article. In evolutionary game model, the average residual energy of each cluster, average intra-cluster energy consumption, and average inter-cluster energy consumption are used to design utility function. The sink will select the cluster with more utility value as its new location and move to the cluster head which has the largest residual energy and the shortest distance to other cluster heads. The simulation results show that the algorithm can effectively balance network load, reduce network energy consumption, prolong the network lifetime, and increase the number of data packets that sink receives.

Keywords
Evolutionary game, mobile sink, wireless sensor networks, trajectory design algorithm, clustering algorithm

Introduction
In the deformation monitoring of tunnels, subways, buildings, bridges, and many other structures, one effective method is to use laser scanning technology. Xu et al.¹ proposed an outlier-resistant and intelligent method for B-spline approximation to deal with outliers and data gaps. Xu et al.² combined terrestrial laser scanning and laser tracker technologies to improve high-accuracy surface modeling in deformation analysis. The other method of deformation monitoring is to use wireless sensor network (WSN) technology. In WSNs, nodes are usually powered by batteries. How to make full use of the energy of nodes to prolong the network lifetime is one of the main challenges.³

Because the data collected by sensor nodes is forwarded to sink by multi-hop routing, the nodes near sink need to forward more data packets and die earlier, which limits the network lifetime. This problem is called the energy hole problem.⁴ In order to solve the problem, Yarinezhad and Hashemi⁵ proposed a fixed parameter tractable (FPT) approximation clustering algorithm to find an energy-efficient path between the cluster heads (CHs) and the sink. Cayirpunar et al.⁶ proposed optimal mobility patterns of multiple sinks. By moving the sink, the forwarding nodes near the sink are changed and then the energy of the nodes can be evenly consumed. Clustering technology can simplify
routing to improve the efficiency of data transmission. Mobile sink technology can effectively solve the problem of energy hole, but it is not easy to form a dynamic route to sink. Therefore, this article uses evolutionary game to combine the two technologies and maximize the network lifetime.

Due to the movement of the sink, the topology of the entire network will change. Finding a new optimal route to the sink at the lowest communication cost is the key to solving the problem. This article designs a path planning algorithm based on evolutionary game for mobile sink. The network is divided into several data acquisition units whose radius is R by clustering algorithm. The new location of sink is calculated by evolutionary game. After the sink node moves to a new location, each cluster member begins to gather data and transmits to CHs. CHs fuse the received data and forward to sink hop by hop. The main contributions of our work are summarized as follows:

1. A clustering algorithm is proposed to divide the network into several data acquisition units, and each data acquisition unit has only one CH. The CH is used to track the location of the mobile sink, and other nodes are responsible for collecting and transmitting data to the corresponding CHs.

2. A trajectory design algorithm based on evolutionary game is proposed for mobile sink. In this algorithm, the utility function is designed by considering the energy consumption among the clusters, the energy consumption within the cluster, and the average residual energy of the cluster. The mobile sink selects the cluster with maximum utility value as its new location, so that sink will move to the CH that has the largest residual energy and the shortest distance to other CHs.

3. The performance of the proposed algorithm is evaluated according to the network lifetime, the network energy consumption, and the total number of data packets which the sink receives.

The rest of this article is organized as follows. Section “Related work” introduces related work. Section “Network model” defines the network model. Section “Algorithm design” describes the algorithm design. Section “Simulations results” analyses simulations results. Finally, section “Conclusion” draws conclusions.

Related work

Route planning for mobile sink is a very challenging problem for the resource-constrained WSNs. Route planning needs to solve three basic problems: when to move, where to move, and how to move reasonably to avoid the impact on data collection. In order to solve these problems, a lot of sink mobility algorithms have been proposed. According to the number of mobile sinks, these algorithms are classified into two categories: single sink mobility and multiple sinks mobility. According to the route of sink mobility, these algorithms are classified into three categories: random moving mode, fixed moving mode, and controllable moving mode.

Random moving mode means that sink moves in a completely random or partially random manner. Yagouta et al. proposed three moving models: random walk, random waypoint, and Gaussian Markov. Low energy adaptive clustering hierarchy (LEACH) clustering protocol is used as a comparison to evaluate the performance of each moving model in different experiments by changing the number of nodes and packet rate. It analyzes throughput, energy expenditure, packet reliability, and packet delay to make an optimal compromise between saving energy and improving service quality. Restuccia and Das proposed a new swarm intelligence–based node choice algorithm for random moving sink to achieve the preset quality of service constraints on throughput and reliability. It mathematically analyzes the algorithm to get the theoretical boundaries on energy expenditure, number of packets transmitted, and convergence time. Liu et al. proposed a data collection method based on semi-random circle. Sink rotates at a certain angle in the given network zone. From the local point of view, the sink’s movement is semi-random, but from the global point of view, the sink’s movement is nearly circular. Because sink moves semi-randomly, the location privacy of sink is effectively protected. Sink moves circularly to ensure that all data can be collected within the specified time limit. Experiments show that this method can improve the data collection rate and energy efficiency of the network. Angelopoulos et al. used random geometric graph model to better capture the geometric proximity of WSNs and proposed a γ-stretched random movement strategy which favors traversing far neighbor nodes to reduce area overlap and accelerate coverage time. Zhang et al. presented a compressed sensing data acquisition strategy based on ring topology. Double compensation compression sensing technology is used to improve the recovery accuracy. Random walk based on ring topology reduces the number of transmission hops and energy consumption.

Compared with the random moving mode, sink in the fixed moving mode gets more restrictions. Sink always moves along the predetermined orbit in the monitoring region to balance the energy consumption of the nodes. Kumar and Dash focused on finding a motion planning scheme for the moving sink when it travels along the fixed trajectory. It proposed an
optimal speed scheduling algorithm with polynomial time complexity to solve maximum data gathering problem from the monitoring area in a given time. Wu et al. proposed a delay-aware energy-efficient routing scheme for path-fixed moving sink, which can achieve a good balance between data transmission latency and network energy consumption. It devised a lightweight sink location calibration method to decrease the control overhead and proposed a reliable fault-tolerant routing scheme to handle location error. Kumar and Dash established the network flow graph model for path-constrained mobile sink to maximize data collection and minimize energy consumption, and developed a min-cost max-flow data gathering algorithm to solve the network flow optimization problem. Wang et al. proposed an efficient clustering algorithm for mobile sink in WSNs, which uses particle swarm optimization (PSO) algorithm to perform virtual clustering during routing process. It executes PSO algorithm to divide the network into $M$ clusters according to the location of nodes, selects the node with the maximum residual energy in the cluster as the CH, and designs the mobile strategy of the sink in network area to gather data. To solve the hot-spot problem, Wang et al. proposed an enhanced energy-efficient data collection algorithm for mobile sink in WSNs. During data communication, nodes can adjust transmission distance to balance the energy consumption of nodes by the distance to the mobile sink. The proposed algorithm designs the protection mechanism to avoid node death too early. When the residual energy of nodes is lower than the threshold value, they will no longer undertake the task of data forwarding, only send the collected data. Sharma et al. proposed a rendezvous-based routing algorithm, where the middle region of network is divided into a vertical stripe and a horizontal stripe with width $w$. The two stripes are called as the rendezvous areas for data transmission. A portion of the backbone nodes in the rendezvous region are constructed into a tree to forward data. Two data communication methods can be used. In the first method, data are transmitted along the tree from the source node to sink. But in the second method, source node sends data directly to sink. The proposed protocol has good performance in data delivery rate, network delay, and energy conservation.

The fixed moving mode is too inflexible to satisfy the real-time communication requirement of WSNs. In the controllable moving mode, sink can independently determine the next moving direction and location by the feedback information of network nodes and adjust the node’s mobile path and rate in real time to ensure the optimal path. Mitra and Sharma proposed an effective virtual grid–based hierarchical routing method for delay-constrained applications. It intelligently chooses moving trajectory of sink according to hops and packet generation rate of the node to reduce the energy expenditure of multi-hop transmission. In a virtual grid, a node is selected as sub-sink that gathers the monitoring data from other nodes, fuses data to save energy, and sends to mobile sink. Koosheshi and Ebadi divided a large-scale network field into many smaller zones. In each zone, a mobile sink collects data from sensor nodes. An unequal clustering algorithm based on fuzzy logic was proposed, which uses the three parameters: distance to rendezvous nodes, residual energy of nodes, and node density. The proposed algorithm optimizes the energy consumption to avoid energy hole problem. Wang et al. deduced route planning problem for sink as a special traveling salesman problem and proposed a new routing planning algorithm which uses variable dimension particle swarm optimization (VDPSO) to accelerate convergence speed. The optimal path of the mobile sink is derived by the evolutionary method of the particles. Ali proposed an efficient harmony search algorithm for dynamically relocating the mobile sink in a clustering network. First, the network is dynamically clustered according to the number of live nodes and the location of nodes to achieve the load balance, and all nodes are divided into the most appropriate clusters. Next, the optimal location of mobile sink is found so that sink is close to all CHs. Sink is relocated in the middle of all CHs to minimize the distance between CHs and sink. Finally, all nodes collect monitoring data and send it to the CHs, and then the CHs aggregate the data and send it to mobile sink. Nitesh et al. proposed a path planning algorithm based on energy density with delay constraints for mobile sink. Mobile sink obtains the energy density of each sensor node and ranks them, and nodes with higher energy density are selected as rendezvous point that will be visited by mobile sink. In order to meet the preset delay limit of data transmission, the number of rendezvous points must be limited to ensure that the path length of mobile sink does not exceed the threshold value. Therefore, set $S$ is used to save the selected rendezvous points. Traveling salesman problem algorithm is applied to select one rendezvous point to join the set $S$ at a time. This process is repeated until the path length of the mobile sink reaches the threshold value. But the algorithm only considers the energy density and transmission delay, not the data acquisition of the sink. In Wang et al. an improved ant colony optimization algorithm was proposed for WSNs with mobile sink. First, the network is divided into many clusters with equal size, and each cluster has a CH. Then, the ant colony algorithm is used to find an optimal path for the sink to move among CHs so as to reduce energy consumption of data communication. The algorithm uses the distance heuristic factor to increase the influence on the next node, so as to avoid falling into the local optimal solution, but there is still a problem of slow convergence speed.
In the process of data acquisition, the prime target of adopting controllable moving mode is to increase the number of data packets received by sink, reduce the energy expenditure, and satisfy delay limitation of data transmission. Controlled mobile mode is more flexible in trajectory design of mobile sink, but more difficult and challenging. Therefore, how to find a best path of sink mobility is very important to prolong the network lifetime and improve network quality of service. By fully considering the average residual energy of each cluster, average intra-cluster energy consumption, and average inter-cluster energy consumption, the article proposes an algorithm based on evolutionary game to find the optimal path of the mobile sink. Because the game is only between the neighbor CHs, the proposed algorithm reduces energy consumption of data communication and has faster convergence speed and better solution than other algorithms.

**Network model**

**Some assumptions**

For convenience, this article assumes that WSNs have the following characteristics:

1. All sensor nodes are randomly distributed in the monitoring area and have unique ID number.
2. Once the nodes are deployed, it cannot move freely. The energy of nodes is limited and cannot be replenished.
3. There is only one sink in the network that has unlimited energy and can move freely.
4. Network lifetime is expressed by rounds.
5. Sensor nodes have the same initial energy.
6. All sensor nodes can obtain the location information by global positioning system (GPS) or location algorithm.

**Energy consumption model**

In this article, we adopt the same energy consumption model as in Bencan et al. The distance between the transmitter and the receiver is a decisive factor in the energy consumption during transmission. The threshold value \( d_0 = \sqrt{E_{fs}/l_{mp}} \) is set. If the distance is greater than the threshold, the energy consumption adopts multi-path attenuation model. Otherwise, the energy consumption adopts free space model. The energy consumption of nodes sending \( l \) bit data to a receiver at a distance of \( d \) is as follows:

\[
E_s(l, d) = \begin{cases} 
1 \cdot E_{elec} + l \cdot \epsilon_{fs} \cdot d^2 & d < d_0 \\
1 \cdot E_{elec} + l \cdot \epsilon_{mp} \cdot d^4 & d \geq d_0
\end{cases}
\]

where \( E_{elec} \) denotes the energy dissipation to drive the transmitter and receiver circuit. \( \epsilon_{fs} \) and \( \epsilon_{mp} \) denote the energy consumed by power amplification for transmitting one-bit data in free space model and multi-path attenuation model, respectively.

To receive \( l \) bit data, the corresponding energy consumption is as follows

\[
E_r(l) = l \cdot E_{elec}
\]

The energy consumed for data fusion is as follows

\[
E_m(m, l) = m \cdot l \cdot E_{DA}
\]

where \( m \) denotes the number of packages fused and \( E_{DA} \) denotes energy consumption for fusing one-bit data.

**Evolutionary game model**

Game theory is a theory used to make decisions, which aims to provide guidance for participants who are faced with different choices. The famous Nash equilibrium in game theory promotes the research of non-cooperative game. Once the Nash equilibrium is reached in the game model, it means that no player can get more utility through other actions. The basis of classical game theory is that when each participant is completely rational, the prediction of the game will be consistent with the actual results. To be fully rational, each node must know the preferred operation of other nodes. However, for some practical reasons, this demand is not always met. For example, because of energy constraints, not every node can receive the information of other nodes. Game theory can be used in situations where every participant is bounded rationality. In recent years, the efforts to explain the evolution of social behavior determined by genetics in biological science have promoted the development of game theory. Generally speaking, in the actual network environment, the assumption of player rationality is not always satisfied. Therefore, evolutionary game theory can be used to solve many problems in WSNs. In this section, we propose a model of trajectory design algorithm for mobile sink based on evolutionary game theory.

After random deployment of nodes in WSNs, the network is divided into many data acquisition units with radius \( R \) by clustering algorithm before each round starts. Each cluster is a data acquisition unit, and the CH transmits data to sink after the CH fuses the data gathered by cluster members.

If the probability of sink moving to cluster is \( p \), then \( p \) cannot be greater than 1. If the sink moves to cluster \( j \), then cluster \( j \) will generate additional energy consumption \( E_{outer}(j) \) as the relay node. The expectation of moving to the cluster is calculated, and the comprehensive utility function is obtained. The cluster with higher residual energy and closer distance from other clusters is selected as the new location of the sink by game
theory, which makes the energy consumption of the whole network more balanced and extends the network lifetime. The expectation of sink moving to cluster \( j \) is

\[
u_{DP}(j) = p \left( a \frac{EN_{avg}(j)}{E_{init}} - b \frac{E_{inner}(j)}{E_{init}} - c \frac{E_{outer}(j)}{E_{init}} \right) + (1 - p) \left( a \frac{EN_{avg}(j)}{E_{init}} - b \frac{E_{inner}(j)}{E_{init}} - c \frac{E_{outer}(j)}{E_{init}} \right)
\]  

(4)

where \( a, b, \) and \( c \) are positive weight factors, \( EN_{avg}(j) \) is the average residual energy of cluster \( j \), \( E_{inner}(j) \) is the average energy consumption in cluster \( j \), \( E_{outer}(j) \) is the average energy consumption of data forwarding after cluster \( j \) is the new location of sink, and \( E_{init} \) is the initial energy of cluster \( j \)

\[EN_{avg}(j) = \frac{1}{Nb} \sum_{i=0}^{Nb-1} EN(i) \]  

(5)

\[E_{inner}(j) = \frac{1}{Nb} \sum_{i=0}^{Nb-1} E_r(i) + \frac{1}{Nb} \sum_{i=0}^{Nb-1} E_s(i) \]  

(6)

\[E_{outer}(j) = \frac{1}{Nb_h} \sum_{k=0}^{Nb_h-1} E_r(k) + \frac{1}{Nb_h} \sum_{k=0}^{Nb_h-1} E_s(k) \]  

(7)

where \( Nb \) is the cluster size and \( EN(i) \) is the residual energy of cluster member \( i \) of cluster \( j \). \( Nb_h \) is the neighbor number of cluster \( j \). \( E_r(i) \) and \( E_s(k) \) are calculated by equation (1). \( E_r(i) \) and \( E_s(k) \) are calculated by equation (2). The expectation that sink will not move to cluster \( j \) is

\[u_{ND}(j) = p \left( a \frac{EN_{avg}(j)}{E_{init}} - b \frac{E_{inner}(j)}{E_{init}} - c \frac{E_{outer}(j)}{E_{init}} \right) + (1 - p) \times 0 \]  

(8)

Based on the above analysis, the utility function of the game model is defined as the average expectation of nodes competing for new location of the sink. The utility function is calculated by equations (4) and (8) as follows

\[u_j = p \times u_{DP}(j) + (1 - p) \times u_{ND}(j)\]

\[= (2p - p^2)a \frac{EN_{avg}(j)}{E_{init}} + (p^2 - 2p)b \frac{E_{inner}(j)}{E_{init}} - cp \frac{E_{outer}(j)}{E_{init}}\]

(9)

Because \( 0 < p < 1 \), so \( 2p - p^2 > 0 \). In the utility function, it means that the more average residual energy cluster \( j \) has, the greater probability it will be selected. In other words, sink tends to choose clusters with higher average residual energy as its new location. If sink moves to a cluster with less average residual energy, the data transmission task of the cluster will be heavier and the energy consumption will be greater, which will accelerate the death of the cluster and cause energy hole in the network. \( E_{outer}(j) \) means that the sink is more likely to select the cluster which has the smallest distance from the other CHs. The energy consumption of data forwarding is positively correlated with the transmission distance between two CH nodes. The shorter the transmission distance between two CH nodes, the lesser the energy consumption of data transmission. Therefore, choosing the appropriate cluster as the new location of sink is not only conducive to saving energy, but also conducive to energy balance of the whole network.

Evolutionary game is repeated. During a certain period of the game, all the participating clusters can observe their own gains. In the next period, they can gain higher gains by changing their strategies. During this period, the strategy change in the participating cluster is determined by the replication dynamic equation, which is expressed as

\[f(j) = \alpha \times p \times (u_{DP}(j) - u_j)\]

\[= \alpha \times \left( p \times (1 - p)^2 \left( a \frac{EN_{avg}(j)}{E_{init}} - b \frac{E_{inner}(j)}{E_{init}} \right) \right)

\[- cp \times (1 - p) \frac{E_{outer}(j)}{E_{init}}\]

(10)

where \( \alpha > 0 \) is the replication dynamic coefficient, \( u_{DP}(j) \) is the expectation that sink will move to cluster \( j \), \( u_j \) is the utility function, and \( p \) is the probability that the sink will move to cluster \( j \).

Based on the above model, the optimal position of the sink is selected by equation (9), which not only minimizes the energy consumption of the CHs in the current round but also achieves the energy balance of the entire network due to the dynamic selection of the sink position. Equation (10) is the replication dynamic equation of the node. It can be seen from equation (10) that the node will adjust its own strategy according to \( E_{outer}(j) \), and finally the participating nodes can converge to a stable state.

**Algorithm design**

The whole algorithm is divided into three parts: cluster setup, sink mobility, and data collection. First, the network is divided into clusters, then the sink moves to the appropriate cluster, and finally data collection is carried out.

**Cluster setup**

Node initialization phase: The main task of this phase is to collect information about each node. Each node sends the HELLO message within the transmission radius \( R \) and gets the number of neighbors within the
transmission radius $R$. The HELLO message includes node ID, residual energy, and node location.

CH election stage: Each node is compared with its neighbor node, and the node with the largest residual energy is selected as the CH. In order to ensure that there is only one CH in each cluster, when the residual energy of two nodes is the same, the CH with smaller node ID is selected.

Cluster formation stage: After the node is elected as the CH, it will broadcast the ADV message including node ID, residual energy, and node location. Ordinary nodes select the CH with the closest distance and the largest residual energy to join in their transmission radius $R$.

Sink mobility

Based on the evolutionary game model, sink tends to choose cluster with the highest average residual energy and the smallest distance to the other CHs as its new location. After the end of one round of data collection, the optimal location of the sink is calculated for the next round of data collection. After clustering, each CH reports its residual energy and location information to sink and plays game with each other. Finally, sink calculates cluster’s utility by equation (9), and the cluster with most utility is selected as new location of the sink. If sink is already in the cluster, it does not move. If sink is not in the cluster, sink moves to the location of new CH. The specific execution process of the algorithm is shown as pseudo code 1.

Data collection

After the mobile sink moves to the next location, the mobile sink communicates with the CHs by broadcasting a REQ message including sink ID and sink position. The CHs near sink re-broadcast REQ message so that all CHs can receive it. Finally, a data forwarding tree to sink is constructed among all CHs. Each cluster member sends the collected data to the CH. The CH fuses and forwards the data to sink hop by hop. When the data acquisition reaches the required number of times, the round ends. All nodes are re-clustered and start the next round. The specific execution process of the algorithm is shown in Figure 1.

Simulation results

The nodes are randomly distributed in a monitoring field with a size of 100 × 100, which is as shown in Figure 2. Hybrid energy-efficient distributed clustering approach (HEED) is a classic protocol of clustered routing protocol, and fuzzy logic based clustering combined with mobile sink (FLBCMS)28 combines mobile sink of fixed path with fuzzy clustering algorithm. Therefore, the two algorithms are chosen for comparison. The simulation parameters are listed in Table 1.

Network lifetime

First, the following indicators are defined to better measure the network lifetime:

FND: it denotes the time when the first sensor node dies.

HND: it denotes the time when half of sensor nodes die.

WND: it denotes the time when the whole network dies (when the number of surviving nodes is less than 30%).

Figure 3 shows the number of surviving nodes in different rounds. Before the whole network dies, the number of surviving nodes in the proposed algorithm (evolutionary game–based trajectory design algorithm (EGTDA)) is higher than that in FLBCMS and HEED, because nodes consume least energy when using EGTDA.

Figure 4 is a comparison of FND, HND, and WND. The FND, HND, and WND of EGTDA are 60.5%, 10.1%, and 4.5% longer than those of FLBCMS, respectively, and are 119.9%, 56.8%, and 53.3% longer than those of HEED, respectively. In HEED, the sink is static, and data are transmitted between the CHs by multiple hops, so the nodes near the sink die quickly because of a lot of forwarding data. In the selection process of CH, FLBCMS and EGTDA overcome the randomness of CH selection, but in FLBCMS sink can only move along fixed path, which puts a heavy load on the nodes on either side of the track, leading to uneven

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**Pseudo code 1: evolutionary game algorithm**

1. While (network is alive)
2.  For (each node $i$)
3.     Node $i$ broadcasts HELLO message
4.   End For
5.  Elect cluster heads
6.  For (each node $j$ $\in$ CH)
7.    Node $j$ broadcasts ADV message
8.  End For
9.  Ordinary nodes join the cluster
10. Sink finds node $j$ $\in$ CH to be moved by equation (9)
11. If ($\sqrt{\left(x_{\text{sink}} - x_j\right)^2 + \left(y_{\text{sink}} - y_j\right)^2} \leq R$) then Sink doesn’t move
12. Else
13.     $x_{\text{sink}} = x_j \cdot y_{\text{sink}} = y_j$
14.     End If
15. Sink broadcasts REQ message
16. Cluster heads generate the path to sink
17. While (the current round $k <$ number of rounds $N$)
18.     Cluster members send the data to cluster head
19.     Cluster head forwards the data to sink
20. End While
21. End While
energy consumption. EGTDA uses autonomous mobile path and chooses the optimal location of sink by considering the residual energy of each cluster and the distance from each CH to sink. Therefore, EGTDA can effectively solve energy hole problem.

**Network energy consumption**

The energy consumption of network in each round is shown in Figure 5. Three algorithms show a linear growth state, but the energy consumption of EGTDA is the smallest.

The standard deviation of residual energy of nodes in each round is shown in Figure 6. It can be seen that the maximum standard deviation of residual energy of EGTDA is smaller than that of FLBCMS and HEED, that is to say, the energy consumption of EGTDA is more balanced.

In HEED, the CH needs multi-hops to transmit data to the static sink, and they consume a large amount of

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**Table 1. Simulation parameters.**

| Parameter       | Value          |
|-----------------|----------------|
| Number of nodes, N | 100            |
| $d_0$          | 87 m           |
| $E_{elec}$     | 50 nJ/bit      |
| $e_{fa}$       | 10 pJ/bit/m$^2$|
| $e_{mp}$       | 0.0013 pJ/bit/m$^4$ |
| $E_{DA}$       | 5 nJ/bit/packet |
| Packet size, l | 4000 bits      |
| $a$            | 0.5            |
| $b$            | 0.25           |
| $c$            | 0.25           |
| Frames/round   | 20             |
| Transmission radius, R | 30 m       |

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**Figure 1.** Execution process of EGTDA.

**Figure 2.** Distribution of nodes.
energy. The nodes near sink undertake more data forwarding tasks, so the energy among nodes is the most unbalanced. In FLBCMS, because the sink is mobile, the number of hops and energy consumption of data forwarding is less than that of HEED. In EGTDA, evolutionary game is used to calculate the optimal path of sink. Because the sink does not move along a fixed path, the amount of data forwarded by different CHs is similar, which makes the energy consumption of nodes least and most balanced.

**Number of packets received by the sink**

Figure 7 shows the number of packets received by the sink. In EGTDA, the sink receives 17.9% and 35.3% more data packets than that in FLBCMS and HEED, and which shows that EGTDA is most stable in the data transmission, because EGTDA has the least and most balanced energy consumption.
Conclusion

Nodes in WSNs are often deployed randomly and intensively. Because nodes transmit data in the form of multi-hops, some nodes are easily overloaded, resulting in uneven energy consumption and network energy hole problem. In this article, mobile sink is used to solve this problem. The network is divided into several data acquisition units by clustering algorithm. By synthetically considering the average residual energy of each cluster, average intra-cluster energy consumption, and average inter-cluster energy consumption, an EGTDA for mobile sink in WSNs is proposed. The experimental results show that in the proposed algorithm, the death time of the first node, the death time of half of the nodes, and the death time of the whole network are 60.5%, 10.1%, and 4.5% longer than those in FLBCMS, respectively, and are 119.9%, 56.8%, and 53.3% longer than those in HEED, respectively.

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