Balancing energy consumption with mobile agents in wireless sensor networks

Kai Lin [a,*], Min Chen [b], Sherali Zeadally [c], Joel J.P.C. Rodrigues [d]

[a] *School of Computer Science and Engineering, Dalian University of Technology, Dalian, Liaoning, China*
[b] *School of Computer Science and Technology, Huazhong University of Science and Technology, China*
[c] *Department of Comp Sci & Info Tech, University of the District of Columbia, Washington, DC 20008, USA*
[d] *Instituto de Telecomunicações, University of Beira Interior, Portugal*

ABSTRACT

For Wireless Sensor Networks (WSNs), an unbalanced energy consumption will decrease the lifetime of network. In this paper, we leverage mobile agent technology to investigate the problem of how to balance the energy consumption during data collection in WSNs. We first demonstrate that for a sensor network with uniform node distribution and constant data reporting, balancing the energy of the whole network cannot be realized when the distribution of data among sensor nodes is unbalanced. We design a method to mitigate the uneven energy dissipation problem by controlling the mobility of agents, which is achieved by an energy prediction strategy to find their positions. Finally, we propose energy balancing cluster routing based on a mobile agent (EBMA) for WSNs. To obtain better performance, the cluster structure is formed based on cellular topology taking into consideration the energy balancing of inter-cluster and intra-cluster environments. Extensive simulation experiments are carried out to evaluate EBMA with several performance criteria. Our simulation results show that EBMA can effectively balance energy consumption and perform high efficiency in large-scale network deployment.

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1. Introduction

Wireless Sensor Networks (WSNs) can collect information and monitor situations in a variety of scenarios including battlefields, forests, farmlands, coal mines, and so on [1–3]. Compared to other self-organized networks, the nodes in WSNs are generally powered by small inexpensive batteries. Each operation, calculation, and inter-communication consumes the nodes' energy. Once some nodes, especially those crucial nodes like the cluster head run out of energy, they will directly influence the connection of WSNs, and the monitoring process. To extend the network's lifetime of power-constrained wireless sensor networks for a long period of time, their energy consumption should be well-managed by optimal routing designs.

As most sensor nodes are unable to communicate with the sink node directly because of their limited communication capacity, multi-hop becomes the basic routing model in WSNs. Under this model, intermediate nodes deplete their energy faster when taking more tasks, such as relaying the received data or completing the fusion process to reduce the network's load, which leads to the creation of an energy hole. Experimental results in [4,5] show that, by

the time the sensors close to the sink exhaust their energy budget, up to 90% of the initial budget may still be available in the nodes farthest away from the sink. Therefore, unbalanced energy consumption is an inherent problem that needs to be solved to avoid early network collapse due to the death of some critical nodes.

The design of energy balancing routing techniques for WSNs has attracted a lot of attention and some valuable results have been reported in recent years [6]. Powell et al. proposed a centralized algorithm to compute the optimal parameters for WSNs and proved that these parameters maximize the network's lifetime [7]. Olariu et al. investigated the theoretical aspects of the uneven energy depletion phenomenon in sink-based wireless sensor networks [8]. Wu et al. explored the theoretical aspects of the non-uniform node distribution strategy that addresses the energy hole problem in WSNs. They proposed a distributed shortest path routing algorithm tailored for the proposed non-uniform node distribution strategy [9]. Zhang et al. formulated the energy consumption balancing problem as an optimal transmitting data distribution problem by combining the ideas of corona-based network division and mixed-routing strategy together with data aggregation [10]. Although the method presented by Wu and Zhang can achieve the energy balance in a certain area, they assume that each node has the same data generation rate. However, this is not the case with most real applications.

In this paper, we investigate the problem of balancing the energy consumption during data collection in WSNs. We design a routing adopting cluster structure which is prior to the flat

* Corresponding author.
E-mail addresses: link@dlut.edu.cn, linkai.dlut@gmail.com (K. Lin), minchen@ieee.org (M. Chen), szeadally@udc.edu (S. Zeadally), joeljr@ieee.org (J.J.P.C. Rodrigues).

structure, as it can extend the network scale and manage the data in distribution. WSNs contains hundreds or thousands of sensor nodes, where the cluster hierarchy is more efficient to manage and run the distributed computation than that of the flat structure. Besides, the abundance of the sensory data among neighbor nodes are increased in the cluster hierarchy, which decreases the amount of transmitted data by the fusion process. Most of the sensor nodes can turn off their communication model to reduce energy consumption under a cluster hierarchy in a quite long period which can prolong the lifetime of the whole network. As the cluster heads play the tasks far more than other ordinary nodes in cluster structure, the resource of cluster heads determines the lifetime of whole network. By introducing special nodes like a mobile agent, it can solve this problem. The more powerful mobile agent is better suited to serve as a cluster head to perform more tasks. We present an energy balancing clustering routing based on mobile agent, which adopts a cellular topology and establishes a virtual tree for data fusion in each cluster. To mitigate the uneven energy dissipation problem, the remaining energy and task allocation of sensor nodes are fully considered during the agent's mobility. We also design a time slot allocation strategy for EBMA to avoid communication conflicts and interruption when many ordinary nodes in one cluster send data to the cluster head simultaneously. The main contributions of this paper are summarized as follows:

- We systemically analyze energy balancing for cluster structures in WSNs. Then we show that the energy balance of intra-cluster and inter-cluster is impossible to achieve in the whole network.
- We design an energy prediction strategy, which enables mobile agents to know about the remaining energy of all sensor nodes in their clusters. Based on this strategy, we propose a solution for determining the position of mobile agents to address the uneven energy dissipation problem.
- We propose an energy balance clustering routing approach based on mobile agent technology, which can efficiently balance the energy consumption of an inter-cluster and an intra-cluster. To obtain better performance, the cluster structure is set up based on cellular topology. Additionally, we allocate individual time slots for each node in a distributed manner to avoid collisions and interference during data gathering.
- We perform extensive simulation experiments to evaluate EBMA by several performance criteria. The results show that EBMA can efficiently balance energy consumption and performs high efficiency in a large-scale network deployment.

The rest of this paper is organized as follows: Section 2 surveys related works. Section 3 presents the problem statement and the system models that can address the problem. Section 4 analyzes sensor networks with a static base station and with a base station moving arbitrarily. Section 5 introduces the energy map with an energy prediction mechanism. An energy balancing cluster routing approach is proposed in Section 6. Simulation results and analysis are provided in Section 7. Finally, Section 8 concludes the paper.

2. Related works

Current approaches for balancing energy consumption in wireless sensor networks can be classified into four categories: data fusion, non-uniform deployment schemes, mobility of sink or agent, and cluster or grid structure.

Krishnamachari et al. investigated the impact of data aggregation by surveying the existing data aggregation protocols in WSNs in [11]. Richkenbach et al. proposed an optimal algorithm MEGA for foreign-coding and an approximating algorithm LEGA for self-coding in [12]. In MEGA, each node sent raw data to its encoding point using a directed minimum spanning tree (DMST), and encoded data was then transmitted to the sink through SPT. Goel

et al. proposed LEGA by using a shallow light tree (SLT) as the data gathering topology in [13]. Luo et al. developed an online algorithm capable of dynamically adjusting the route structure when sensor nodes joined or left the network in [14]. Furthermore, by only performing such reconstructions locally and maximally preserving the existing routing structure, the online algorithm could be readily implemented in real networks in a distributed manner and promised extremely small performance deviation from the offline version and outperformed other routing schemes with static aggregation decisions. Anandkumar et al. presented a novel formulation for optimal sensor selection and in-network fusion for distributed inference known as the Prize-Collecting Data Fusion (PCDF) in terms of optimal trade-off between the costs of aggregating the selected set of sensor measurements and the resulting inference performance at the fusion center [15]. PCDF is then analyzed under a correlation model specified by a Markov random field (MRF) with a given dependency graph. For a special class of dependency graphs, a constrained version of the PCDF reduces to the prize-collecting Steiner tree on an augmented graph. In this case, an approximation algorithm is given with the approximation ratio depending only on the number of profitable cliques in the dependency graph. Luo et al. found that fusion costs were comparable to those of communications for certain applications in [16]. Motivated by the limitations of a minimum fusion Steiner tree, they designed a novel routing algorithm, called the Adaptive Fusion Steiner Tree (AFST) for energy efficient data gathering in sensor networks.

Xing et al. bridged the gap between sensing coverage and the stochastic nature of sensing. The scaling laws were derived between coverage, network density, and signal to noise ratio in [17]. Giridhar et al. first focused on analytically solving the linear program for some simple regular network topologies in [18]. They found an upper bound on the functional lifetime for the linear case, and upper and lower bounds on the functional lifetime are only different for a regular planar network. Li et al. investigated the problem of uneven energy consumption in a large class of many-to-one sensor networks and verified that nodes in inner rings suffer much faster energy consumption rates [19]. They studied the effectiveness of several existing approaches towards mitigating the "energy hole" problem, including deployment assistance, traffic compression and aggregation. Zhang et al. formulate the energy consumption balancing problem as an optimal transmitting data distribution problem by combining the ideas of a corona-based network division and mixed-routing strategy together with data aggregation [10]. Wu et al. proved that suboptimal balanced energy consumption is attainable only if the number of nodes grows with geometric proportion from the outer coronas to the inner ones except the outermost one [20].

Some researchers have explored approaches to minimize the energy consumption difference between nodes. Many moving strategies for sink nodes or agents are presented to balance the energy consumption. Gandham et al. analyzed this problem and presented a model that combines data routing with station mobility to enable load balancing [21]. This strategy can only support the data collection based on inquiry and not reduce the energy load. Wang et al. changed the station mobility model to a linear plan for the optimized station mobility and special stop point [22]. Shah et al. presented a data mule, which can complete the data transmission by mule mobility [23]. The load in this method is small but the real-time data cannot be guaranteed. Wang et al. presented a data gathering model by agent mobility, where the station is stable and the agents distributed among the stations move around the circle [24]. This method cannot solve the node load balance over two hops.

Heinzelman et al. proposed a low energy adaptive clustering hierarchy (LEACH) for WMSNs in [25]. Since then, the clustering

routing plays an important and essential role in the routing of WSNs. However, LEACH cannot guarantee either the position or the number of clusters in the network. Besides, it does not fully consider the energy of sensor nodes during the selection of cluster head nodes. Xu et al. proposed GAF to divide the coverage area into squares and considered the nodes in a square to be equivalent for routing in [26]. Wang et al. proposed SoRCA to implement self-healing, but it partitions the working area into fixed hexagons, and considers each hexagon to be fully covered if there is one active node within the cell in [27]. Liu and Chang et al. proposed GAF-h and ZBP to take the advantage of hexagon-like cellular instead of square topology, but they are not suitable in random deployment of nodes in practice [28,29]. These four clustering routing approaches only consider the position of sensor nodes but ignore the energy level of the candidate cluster head node. Besides, each sensor node has to know its accurate position to form the cellular structure. It cannot meet the low cost requirement of WSNs. Wu et al. explore the theoretical aspects of the non-uniform node distribution strategy that addresses the energy hole problem in WSNs. They propose a distributed shortest path routing algorithm tailored for the proposed non-uniform node distribution strategy [30]. Lin et al. proposes a clustering hierarchy based on cellular topology (CHCT) for WSNs, in which the remaining energy and position of sensor nodes are simultaneously considered during the cluster structure construction, and the desired cluster structure is generated even in the case of nodes without a locating device [31].

3. System models and problem statement

3.1. System models

3.1.1. Network model

We assume a relatively dense and strongly connected network that harvests data from the area covered by the network. The network consists of a set n of static sensor nodes, denoted by $s_1, s_2, \ldots, s_n$, which is used for collecting sensory data. All sensor nodes are uniformly distributed in a monitoring area with only one sink located as the final destination of data collected. Except for ordinary sensor nodes and the sink, there are still m mobile agents, denoted by $a_1, a_2, \ldots, a_m$. Mobile agents can control their movement paths, collect the data sent from sensor nodes and send to the sink node after processing. The communication ability of mobile agents is much higher than ordinary sensor nodes, and they are not limited by the energy supply as the sink node is. In our research, we focus only on the communications among the sensor nodes, the mobile agents and the sink node. Communications between the sink node and devices outside the network are beyond the scope of this paper.

3.1.2. Fusion model

In this work, we also consider data fusion during data collection. Similar to Ref. [32], we use data fusion model, where the sensor nodes are required to continuously send their data. A node u needs to receive the sensory data sent from node v, marked as $D(v)$. The total data amount after fusing $D(u)$ and $D(v)$ is expressed as:

$$\widetilde{D}(u) = \max(D(u), D(v)) + \min(D(u), D(v))(1 - \rho) \tag{1}$$

where $D(u)$ and $\widetilde{D}(u)$ represent the data amount before and after data fusion, respectively. ρ represents the correlation coefficient of $D(u)$ and $D(v)$. Based on Eq. (1), the data amount after fusion will not be larger than the sum of $D(u)$ and $D(v)$, and not smaller than the either the maximum of $D(u)$ or $D(v)$.

3.1.3. Energy model

We assume that all the ordinary sensor nodes have the same initial energy while both the sink node and mobile node are not
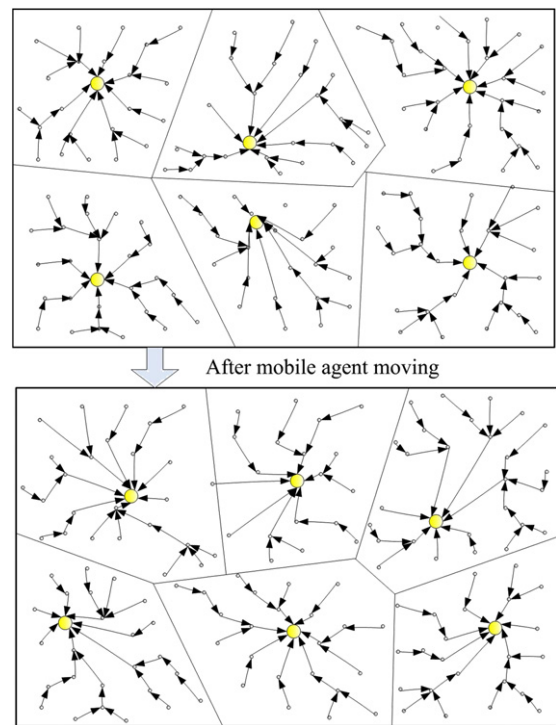

Fig. 1. Example of data gathering in WSNs with mobile agent.

limited by energy supply. The energy spent by transmitting 1 bit data over distance d is $e_t(d) = \varepsilon_{\text{elec}} + \varepsilon_{\text{amp}}d^k$, where $\varepsilon_{\text{elec}}$ is the energy spent by the transmitter electronics, ε_{amp} is the transmitting amplifier and $k(k \geq 2)$ is the propagation loss exponent [33]. $\varepsilon_{\text{elec}}$ and ε_{amp} are both system parameters. The corresponding energy dissipation in data reception is $e_r = \varepsilon_{\text{elec}}$. The data fusion process can introduce additional energy consumption, which is denoted by e_f.

3.2. Problem statement

In the network's structure we adopted, the clusters named as $C_1, C_2, \ldots, C_N$, are obtained by partitioning the whole network. Each cluster has a mobile agent denoted as the cluster head. The area of C_i is denoted by $S_i(1 \leq i \leq N)$. As the price of mobile agent is higher than ordinary nodes, the number of them in the network should be as low as possible to reduce costs. Each mobile agent needs to manage a large area which results in some sensor nodes not being able to communicate with them directly because of the long distance. As shown in Fig. 1, there are many multi-hop routes built for intra-cluster data gathering. Depending on the distance from the mobile agent, each sensor node can determine its hop count, where the hop count for directly communicating with mobile agent is 1. For any node $u \in C_i$, it has to forward the data received from the child node to the parent node. The different loads among nodes is the main reason for the occurrence of energy holes.

We assume that all the sensor nodes generate data at the same rate and the size of each data packet is same. All nodes use the same transmission radius which is lower than the communication distance to the mobile agent. Although the amount of data generated by each node is the same during some time period, the data distribution is still unbalanced since each node performs different tasks.

Based on the above model, our optimization objective is to balance the energy consumption to the maximum while collecting

data from all sensor nodes and delivering the data to the sink node. This problem can be formulated as follows:

$$
\begin{cases}
\min \sum_{u \in M}[E_l(u) - \bar{E}_l]^2 \\
\text{s.t.} \sum_{i \in [1,N]} S_i = S \\
\quad T_u \leq T_d
\end{cases}
\tag{2}
$$

where $E_l(u)$ represents the remaining energy of node u. $\bar{E}_l$ represents the average of the remaining energy of all sensor nodes. T_u represents the time it takes to send data from node u to the sink node. T_d represents the maximum allowed transmission delay.

In (4), the first constraint specifies the total area of network S. The second constraint specifies that the essential requirement is the real-time request of data collection. The above optimization problem can be solved as two sub-problems:

- How to balance energy consumption among nodes within each cluster? We refer to this problem as intra-cluster energy consumption balancing.
- How to balance energy consumption among nodes belonging to different clusters? We refer to this problem as inter-cluster energy consumption balancing.

It will be described in detail in the following section.

4. Energy balancing problem for hierarchical clusters

This section focuses on the analysis of energy balancing problem in WSNs under cluster hierarchy which deals with both inter-cluster and intra-cluster. A sufficient and necessary condition of energy balancing is presented. It is proven that the energy consumption among sensor nodes cannot be balanced if the multi-hop of an intra-cluster is adopted.

4.1. Energy balancing of intra-cluster

As mentioned above, the mobile agent approach is more expensive than when using ordinary sensor nodes, which is not suitable for large network deployments. As a result, the cluster area is generally large, which needs to complete the data collection through multi-hop communications of the intra-cluster. We assume that the boundary of the cluster is circular for easier description. As shown in Fig. 2, the cluster C_i is divided into p zones $C_{i,1}, C_{i,2}, \ldots, C_{i,p}$, which need to guarantee that the sensor nodes in two adjacent sub-zones can communicate directly. Consider any two adjacent coronas $C_{i,k}$ and $C_{i,k+1}$ where nodes in $C_{i,k+1}$ forward their data to nodes in $C_{i,k}$ when hop-by-hop transmission mode is used. $C_{i,k+1}$ is termed as the source zone and $C_{i,k}$ is termed as the destination zone.

For every node u in cluster C_i, let $E(u)$ denote the total amount of energy depleted by u during time T for data gathering. Using the energy model given in Section 3.1.3,

$$
E(u) = D_T(u)e_t(r) + D_R(u)e_r(r) + D_F(u)e_f
\tag{3}
$$

where $D_T(u), D_R(u), D_F(u)$ denote the total amount of data received, transmitted and fused by node u respectively. The first term $D_T(u)e_t(r)$ represents the energy spent by data transmission, the second term $D_R(u)e_r(r)$ represents the energy spent by receiving data and the last term $D_R(u)e_r(r)$ is the energy consumption for data fusion. The energy consumption is balanced among all nodes in cluster C_i only when

$$
E(u) = E(v), \quad \forall u, v \in C_i.
\tag{4}
$$

The total amount of data fused by node u is:

$$
D_F(u) = D_S(u) + D_R(u).
\tag{5}
$$

From the fusion model given in Section 3.2, the total amount of data transmitted by node u after fusion can be calculated as:

$$
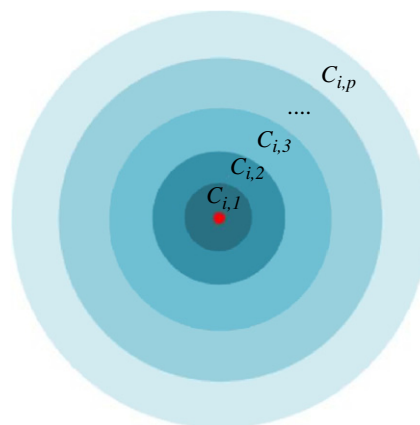D_T(u) = \max(D_R(u), D_S(u)) + \min(D_R(u), D_S(u))(1 - \rho).
\tag{6}
$$

Fig. 2. A cluster consisting of a series of zone.

Theorem 1. *Energy consumption is unbalanced among nodes in cluster C_i if multi-hop communication is adopted.*

Proof. When the area of C_i is small enough, all nodes in C_i can communicate with the cluster head directly. For $\forall u \in C_i$,

$$
D_R(u) = D_F(u) = 0
\tag{7}
$$

$$
\begin{aligned}
E(u) &= D_T(u)e_t + D_R e_r + D_F(u)e_f \\
&= D_S(u)e_t.
\end{aligned}
\tag{8}
$$

Therefore, the energy consumption can be balanced among nodes in C_i only if the amount of data generated by sensor nodes is balanced.

When the area of C_i is larger and the multi-hop approach needs to be adopted, the energy consumption of the sensor nodes with the maximum number of hops for the other sensor nodes is similar to the equation above. For the other nodes,

$$
\begin{aligned}
E(u) &= D_T(u)e_t + D_R e_r + D_F(u)e_f \\
&= [\max(D_S(u), D_R(u)) \\
&\quad + \min(D_S(u), D_R(u))(1 - \rho)]e_t \\
&\quad + D_R(u)e_r + [D_R(u) + D_S(u)]e_f.
\end{aligned}
\tag{9}
$$

It can be deduced as:

$$
E(u) = \begin{cases}
D_R(u)[(1 - \rho)e_t + e_r + e_f] + D_S(u)(e_f + e_t), \\
\quad D_S(u) > D_R(u) \\
D_R(u)(e_t + e_r + e_f) + D_S(u)[(1 - \rho)e_t + e_f], \\
\quad TD_S(u) \leq D_R(u)
\end{cases}
\tag{10}
$$

$E(u)$ depends on $D_R(u)$ and $D_S(u)$ as all the other parameters are the same for all nodes in C_i. We assume that v and w is the child and parent node of node u, respectively. $D_R(v) < D_R(u) < D_R(w)$. Hence, the energy balancing cannot be realized in C_i with the random data generating model. The theorem is thus proved. □

4.2. Energy balancing of inter-cluster

Let S_i and E_i denote the area of cluster C_i and the total energy consumed per unit time by all the nodes in cluster C_i. As described in Section 3.1, all the sensor nodes are homogenously distributed and the density is ρ. When all the sensor nodes are equipped with the same initial energy, the energy balancing of the inter-cluster between C_i and C_j is obtained if and only if it satisfies the following equation:

$$
\frac{S_i \rho E_0}{E_i} = \frac{S_j \rho E_0}{E_j} \quad \forall i, j \in (1, 2, \ldots, N)
\tag{11}
$$

where E_0 is the initial energy of each node. The inter-cluster energy balancing cannot be achieved either as we have proved that intra-cluster energy balancing is impossible when multi-hop communication is adopted.

Theorem 2. *When the sensor nodes are uniformly distributed, the energy balancing of the inter-cluster is unrealizable if the multi-hop communication is adopted.*

Proof. For $\forall u \in C_{i,p}$, it only needs to transmit its sensory data to its forwarding node in $C_{i,p-1}$. For $\forall u \in C_{i,k}, k \in [1, 2, \ldots, p-1]$, it needs to receive, fuse and transmit the data. Here, the energy consumption of node u can be calculated as:

$$E(u) = \begin{cases} D_T(u)e_t = D_S(u)e_t \forall u \in C_{i,p} \\ \quad = [\max(D_S(u), D_R(u)) \\ \quad + \min(D_S(u), D(R)(u))(1-\rho)e_t \\ \quad + D_R(u)e_r + D_S(u)]e_f \\ \forall u \in C_{i,k}, \quad k \in [1, 2, \ldots, p-1] \end{cases} \tag{12}$$

The total energy consumption of all nodes in C_i can be calculated as:

$$E_i = \sum_{u \in C_{i,p}} D_S(u)e_t + \sum_{k=1}^{p-1} \sum_{u \in C_{i,k}} ([\max(D_S(u), D_R(u))$$

$$+ \min(D_S(u), D_R(u)(1-))]e_t) + D_R(u) + D_S(u)e_f. \tag{13}$$

According to the Eq. (13), the energy balancing between cluster C_i should meet the following condition:

$$S_i E_j = S_j E_i. \tag{14}$$

When the cluster is formed, both S_i and S_j are constant. E_i and E_j are determined by $D_R(u)$ and $D_S(u)$. The movement of the mobile agent results in the changing of $D_R(u)$, which does not satisfy Eq. (14). Therefore, Theorem 2 is now proved. □

5. Energy map and prediction mechanism

In Section 4, we prove that the energy balancing of both inter-cluster and intra-cluster cannot be achieved when a multi-hop communication approach for an inter-cluster is adopted. In order to balance the energy consumption, we focus on the establishment of a local energy map to make the mobile agent aware of the remaining energy of all nodes in its cluster which can provide the necessary information for the mobile agent by determining its movement. However, to become aware of the energy among nodes is difficult to achieve in WSNs because of the high communication costs generated by frequently updating their remaining energy information. Additionally, other issues arise such as network congestion and transmission delay. To address this problem, we adopt an energy prediction mechanism, which can make the mobile agent aware of the remaining energy of all sensor nodes in its cluster by frequent information updating.

Each mobile agent acts as a cluster head, which is responsible for data gathering and establishing the energy map of its cluster. According to Eq. (12), the energy consumption of a sensor node is not stable during data gathering and is determined by its working state. Sensor nodes can turn to a sleep mode when they do not have any task which is necessary to save energy for WSNs, but it also makes it more difficult to predict. As described in Section 3.1, the energy is mainly consumed on receiving, transmitting, and fusing data in our research, where the energy consumption on sensing data and other simple processing can be neglected.

Based on this state conversion model, we can enable energy awareness among nodes. Similar to [34], we use Markov chain to simulate the working states of sensor nodes. Each node has a series of random variants $X_0, X_1, X_2, \ldots$, which describes different working states. P_{ij} is defined as a one-step diversion probability, which can be expressed by:

$$Pij = P\{X_{m+1}|x_m = i\}. \tag{15}$$

The N-step diversion probability is further defined as:

$$P_{ij}(n) = \sum_{k=1}^{M} P_{ik}(r)P_{kj}(n-r), \quad \text{for } 0 \leq r \leq n. \tag{16}$$

If the node is currently in state i, the number of time-slots that it will stay in state s in the next T time-step can be expressed as $\sum_{t=1}^{T} P_{is}(t)$. We use E_s for representing the energy consumption of a node staying at state s in one time-step with one bit of data. Then, the total energy consumption in the next T time-step can be calculated as follows:

$$E_T = \sum_{s=1}^{M} \left(\sum_{t=1}^{T} P_{is}(t) \right) E_s D_s(t) \tag{17}$$

where $D_s(t)$ is the data amount need to be processed at state s. Based on the statistics of working states, the nodes can calculate their own energy consumption or of other nodes in the next T time-step using Eq. (17). Let $S = 1, 2, 3$ represent the node during transmission, reception, and the fusion states. Then the energy consumption of sensor node is:

$$E_T(u) = \left(\sum_{t=1}^{T} P_{i1}(t) \right) D_T(u)e_t + \left(\sum_{t=1}^{T} P_{i2}(t) \right) D_R(u)e_r$$

$$+ \left(\sum_{t=1}^{T} P_{i3}(t) \right) D_F(u)e_f. \tag{18}$$

The accuracy of energy prediction is affected by the validity of the probability diversion matrix. It should be noted that there must be a deviation between the predicted and the actual value. A threshold is necessary to determine whether it needs to recalculate E_T when the deviation exceeds the threshold.

6. EBMA protocol architecture

In this section, we propose an energy balancing cluster routing based on mobile agent (EBMA) for WSNs. The above-mentioned energy prediction mechanism is employed in EBMA. To obtain better performance, the cluster structure is formed based on a cellular topology. The design objective of EBMA is to maximize the balancing of energy consumption among sensor nodes.

6.1. EBMA routing in WSNs

In EBMA, the ordinary nodes connect to the closest mobile agent which can form many clusters. Each cluster has only one mobile agent which acts as cluster head and is responsible for managing all sensor nodes in that cluster. To reduce the number of mobile agents, each mobile agent has to manage the cluster over a large area which requires that multi-hop communication be adopted in cluster. As the mobile agent is not limited by energy supply and communication distance, EBMA has the following two properties:

- The selection of cluster head is not necessary although it is a challenge for traditional cluster routing of WSNs. EBMA avoids the extra cost of communication and computation to determine the cluster head.
- The division of a cluster is easier to do with EBMA. By using a mobile agent to form a special and stable cluster structure, such as cellular topology, the range of cluster can be adjusted freely to be in the range of the mobile agent communication distance.

To obtain better performance, EBMA segments the whole network into regular hexagons according to the location of each
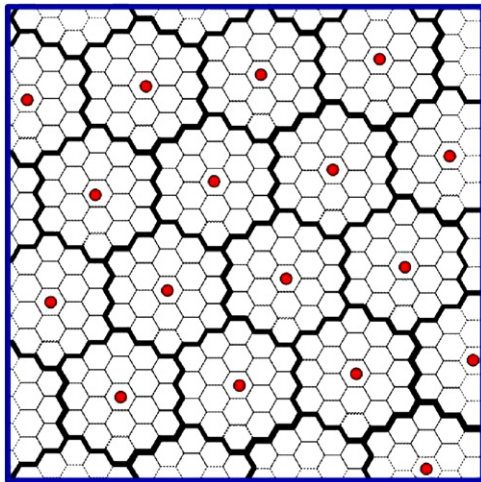
Fig. 3. Cluster distribution based on cellular topology.

node and obtains the cellular topology shown in Fig. 3. Each cluster consists of many hexagon cells. The yellow points in the hexagon act as mobile agents and the rest as ordinary sensor nodes which must join to one of the clusters. The mobile agent is responsible for the management of all sensor nodes and needs to remain active, while the ordinary sensor nodes can turn to a sleep state when they have no tasks to perform. Two kinds of transmission power are adopted: the higher transmission power guarantees the communication of the inter-cluster among mobile agents, while the lower transmission power is used for intra-cluster communication.

To reduce cost, the number of mobile agents should be as low as possible but must guarantee efficient data gathering. In this work, we consider not only the number of mobile agent but also the need to meet the two constraints of Eq. (4). We assume that there are N sensor nodes and M mobile agents. The area of each hexagon cell is S_k. The following lemma gives the allowed number of mobile agents.

Lemma 1. *The number of mobile agent should meet the equation:* $\frac{\tau S}{3(2T+3\tau)} \le M \le \frac{S}{S_k}$. *where τ is the forward relay time.*

Proof. As each cluster consists of at least one hexagon cell, the number of clusters is S/S_k. Additionally, each cluster has only one mobile agent, then $M \le \frac{S}{S_k}$.

To meet the real time requirement of data gathering, the highest level n of hexagon cell should be:

$$(n-2)\tau \le T \Longrightarrow n \le \frac{T}{\tau} + 2. \tag{19}$$

The maximum area of each hexagon cell is $S_c = 3(2n-1)S_k \le 3\left(\frac{2T}{\tau}\right) + 3S_k$.

$$M \ge \frac{S}{S_c}$$

$$= \frac{\tau S}{3(2T+3\tau)S_k}. \tag{20}$$

Therefore, $\frac{\tau S}{3(2T+3\tau)S_k} \le M \le \frac{S}{S_k}$.

Lemma 1 is proved. □

Robust multi-hop routes are formed among hexagon cells to guarantee that the external data generated by the farthest node is transmitted to the mobile agent. As shown in Fig. 4, the data gathering of the inter-cluster starts from the hexagon cell with the highest level and ends when all data are transmitted to the mobile agent. A one-to-one or many-to-one mapping is formed between adjacent cells and data transfer is performed
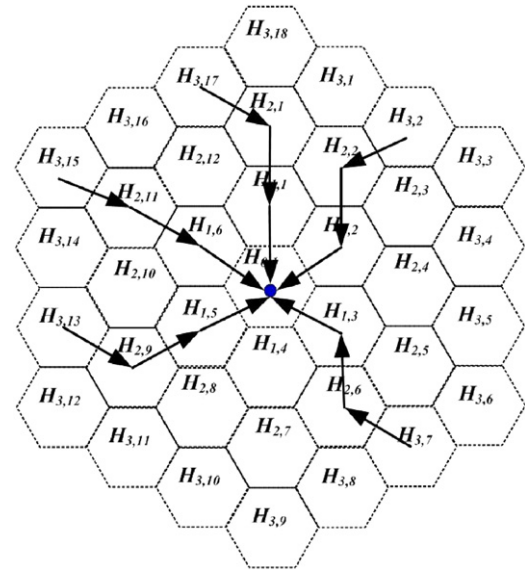

Fig. 4. Example of data gathering in cluster.

between them. In this way, each hexagon cell with level i needs to select one corresponding destination cell from the neighbor cells with level $i-1$. The cell with the highest remaining energy should be selected. All nodes in $H_{i,m}$ forward their data to the nodes in the corresponding destination cell $H_{i-1,n}$. In this case, i belongs to $[1, N]$. $H_{i,m}$ acts as a source cell, and $H_{i-1,n}$ acts as the corresponding destination for $H_{i,m}$. This scheme can effectively reduce data collisions between the neighbor cells.

6.2. Realization of energy balancing

As described in Section 3.2, the optimization target of Eq. (4) can be transformed into two sub-targets: inter-cluster and intra-cluster energy balancing, which can be described as:

$$\begin{cases} \min \sum_{u \in C_i} |E_l^2(u) - \bar{E}_l(i)^2| \\ \min \sum_{i=1}^{L} |\bar{E}_l^2(i) - \bar{E}_l^2| \end{cases} \tag{21}$$

where $\bar{E}_l$ represents the average remaining energy of all sensor nodes, $\bar{E}_l(i)$ represents the average remaining energy of all nodes in cluster i.

Although Theorem 1 has proved that the energy balancing of intra-cluster nodes cannot be achieved when the multi-hop transmission is adopted, it also indicates that the position of the mobile agent can determine the task distribution of sensor nodes. EBMA focuses on computing the optimized location for each mobile agent to balance the energy consumption to the maximum among sensor nodes. The following lemma can minimize the selection range which in turn reduces the complexity of calculation greatly.

Lemma 2. *The location of mobile agents, which can balance energy consumption among sensor nodes to a maximum, must be at the cross-point of three neighbor hexagon cells.*

Proof. The node much closer to the mobile agent needs to take more tasks, which results in an unbalanced distribution of the amount of data.

As shown in Fig. 5, the points A, B, and C represent three different positions of mobile agents. Here, we use S_A, S_B and S_C to represent the area where the energy consumption is consumed fastest in the cluster. E_A, E_B and E_C represent the energy consumption of these zones. These zones are composed of hexagon
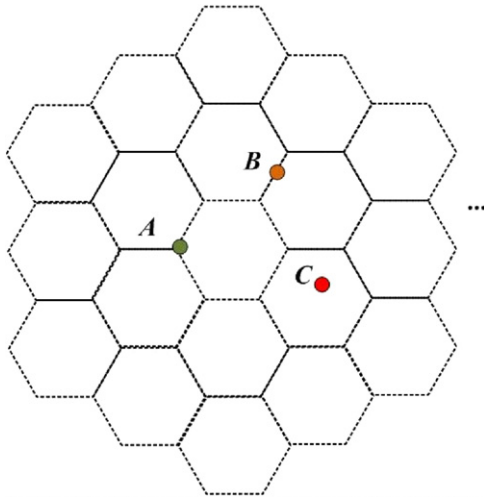
Fig. 5. Different position of mobile agent.

cells which are close to mobile the agent and take most of the tasks. The total amount of data of these zones are denoted as $\sum D(u)$, $\sum D(v)$ and $\sum D(w)$.

When the mobile agent is at the cross-point of three hexagon cells, the sensor nodes in the three hexagon cells do not need to receive data and only need to send sensory data to the mobile agent. There are nine hexagon cells that can communicate with the mobile agent which is responsible for the retransmission of the data from far distances.

$$\frac{S_A \rho E_0}{E_A} = \frac{9 S_e \rho E_0}{E_A}. \tag{22}$$

When the mobile agent moves to the cross point B of two hexagon cells, the nodes in the two hexagon cells do not need to receive data.

$$\frac{S_B \rho E_0}{E_B} = \frac{8 S_e \rho E_0}{E_B}. \tag{23}$$

When the mobile agent moves to the intersection point C of a hexagon cell, the node in this hexagon cell does not need to receive data, which is only responsible for sending sensory data to the agent. There are 6 hexagon cells that can directly communicate with the mobile agent.

$$\frac{S_C \rho E_0}{E_C} = \frac{6 S_e \rho E_0}{E_C}. \tag{24}$$

For $S - S_A - 3S_e < S - S_B - 2S_e < S - S_C - S_e$ we substitute $\sum D_R(u) < \sum D_R(v) < \sum D_R(w)$ into the following equation:

$$
\begin{aligned}
E(i) = {} & \sum_{u \in C_{i,p}} D_S(u) e_t + D_R(u) e_r + D_S(u) e_f \\
& + \sum_{k=1}^{p-1} \sum_{u \in C_{i,k}} [\max(D_S(u), D_R(u)) \\
& + \min(D_S(u), D_R(u)(1 - \rho))].
\end{aligned}
\tag{25}
$$

After simplification,

$$\frac{S_A \rho E_0}{E_A} > \frac{S_B \rho E_0}{E_B} > \frac{S_C \rho E_0}{E_C}. \tag{26}$$

When the location of mobile agents is at point A, which is most beneficial for balancing the energy consumption of different hexagon cells in cluster. Lemma 2 is proved. □

By Lemma 2, it is not necessary for EBMA to consider and compare other positions which can greatly reduce the complexity of the algorithm.

Lemma 3. $\forall u, v \in N, Ec(u) > Ec(v)$, the energy balancing can be realized if and only if the node u takes more tasks than node v.

Proof. If E denotes the energy consumption of those tasks need to be finished, the remaining energy of node u after finishing these tasks that can be calculated as:

$$E_l(u) = E_c(u) - E. \tag{27}$$

Therefore $[E_l(u) - \bar{E}_l]^2 = [E_c(u) - E - \bar{E}_l]^2$, for $E_c(u) > E_c(v)$, it is obviously that $[E_c(u) - E - \bar{E}_l]^2 + [E_c(v) - \bar{E}_l]^2 < [E_c(u) - \bar{E}_l]^2 + [E_v(u) - E - \bar{E}_l]^2$.

The nodes with more remaining energy take the tasks among sensor nodes and they can balance the energy consumption. Lemma 3 is proved. □

By Lemma 3, the mobile agent in cluster C_i should find the optimized position from the cross-point J_i of all three hexagon cells, which can allocate more tasks for those nodes with more remaining energy. To achieve the first optimization target of Eq. (21), EBMA needs to compare the energy consumption difference of sensor nodes when the mobile agent is at a different position of J_i. Using Eq. (4), the proper position can be found to balance the energy consumption where $E_l(u)$ can be calculated by Eq. (17).

Although absolute energy balancing cannot be realized in the whole cluster, it still can be achieved in each hexagon cell. The following lemma gives the condition of energy balancing in a hexagon cell.

Lemma 4. Energy consumption is balanced among nodes in H_i if and only if $D_R(u) = D_R(v)$, $\forall u, v \in H_i$.

Proof. Since all nodes in the network have the same data generation rate (L bit/s), the total amount of data generated by each node during time T is TL. For

$$D_F(u) = D_R(u) + TL \tag{28}$$

$$D_T(u) = \begin{cases} TL(1 - \sigma) + D_R(u), & TL \le D_R(u) \\ TL + D_R(u)(1 - \sigma), & TL > D_R(u). \end{cases} \tag{29}$$

Therefore, the energy consumption of node u is:

$$E_{Ti}(u) = \begin{cases} TL[(1 - \sigma)(e_t + e_s) + e_f] \\ \quad + D_R(u)(e_t + e_s + e_r + e_f), \\ \quad TL \le D_R(u)TL(e_t + e_s + e_f) \\ \quad + D_R(u)[(1 - \sigma)(e_t + e_s) + e_f], \\ \quad TL > D_R(u) \end{cases} \tag{30}$$

$E(u)$ is only dependent on $D_R(u)$ since all the other parameters are the same for the nodes in C_i. Thus, the energy consumption is balanced among nodes in C_i if and only if all nodes in C_i receive the same amount of data. Lemma 4 is proven. □

By Lemma 4, the energy balancing of intra-cell can be realized by equally distributing the amount of data received by nodes in the same cell.

Now, we focus on how to solve the second objective of Eq. (21). The following lemma gives the condition which can meet the energy balancing for an inter-cluster.

Lemma 5. The energy balancing of inter-clusters can be achieved if and only if $\dfrac{S_i}{S_j} = \dfrac{\bar{E}_j \sum_{u \in C_i} \sum_{s=1}^{M} \left(\sum_{t=1}^{T} P_{is}(t) \right) E_s(u) D_{ts}(u)}{\bar{E}_i \sum_{u \in C_i} \sum_{s=1}^{M} \left(\sum_{t=1}^{T} P_{is}(t) \right) E_s(v) D_{ts}(v)}$

Proof. According to Eq. (11), the energy consumption can be balanced in cluster C_i and C_j when

$$\frac{S_i \rho \bar{E}_i}{\sum_{u \in C_i} E_T(u)} = \frac{S_j \rho \bar{E}_j}{\sum_{v \in C_j} E_T(v)}$$

$$\implies \frac{S_i}{S_j} = \frac{\bar{E}_j \sum_{u \in C_i} E_T(u)}{\bar{E}_i \sum_{v \in C_j} E_T(v)}. \tag{31}$$
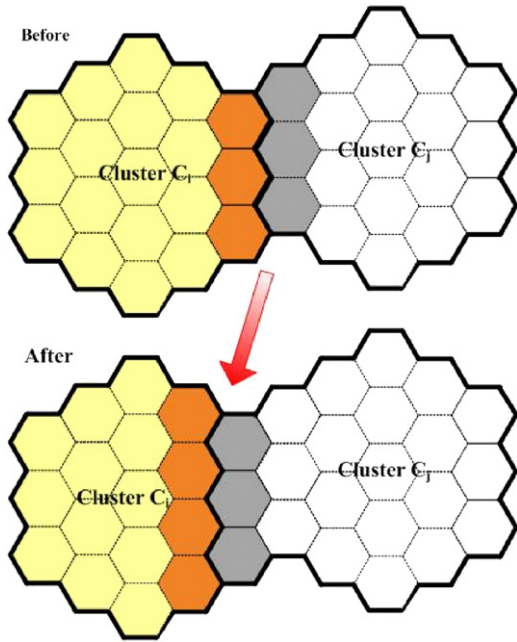
Fig. 6. Different position of mobile agent.

Fig. 8. Operation procedure of EBMA.

Substituting into Eq. (19), then

$$\frac{S_i}{S_j} = \frac{\bar{E}_j \sum\limits_{u \in C_i} \sum\limits_{s=1}^{M} \left(\sum\limits_{t=1}^{T} P_{is}(t) \right) E_s(u) D_{ts}(u)}{\bar{E}_i \sum\limits_{v \in C_j} \sum\limits_{s=1}^{M} \left(\sum\limits_{t=1}^{T} P_{is}(t) \right) E_s(v) D_{ts}(v)}. \tag{32}$$

Lemma 5 is proved. □

As the position changes of the mobile agent cause the hop difference to fulfill data gathering, the variable hops of data gathering in the cluster adopted will result in the changing of $D_{ts}(u)$ and $D_{ts}(v)$. Hence, intra-cluster energy balancing cannot be achieved. However, we can adjust the cluster area to balance the energy consumption.

As shown in Fig. 6, the energy consumptions of the neighboring clusters in EBMA are different. When the average remaining energy of two neighboring clusters is above the set threshold, the neighboring cells in the cluster with lower average of remaining energy will join in the cluster with higher remaining energy. The reduction of cell number decreases the number of hops for data transmissions, which can decrease the total energy consumption in the cluster. The energy consumption of the cluster can be increased by adding more cells. The energy consumption of two neighboring clusters can be balanced by adjusting the cell number.

6.3. Time-slot allocation and state conversion model

It is required to make a node turn to a sleep mode to save energy consumption when the sensor node does not have any task. In EBMA, the operatio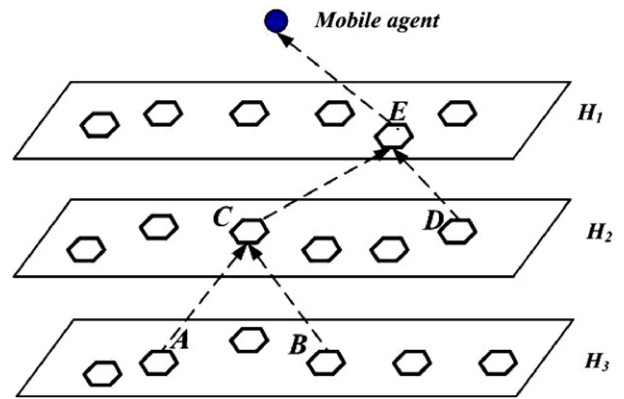n of a sensor node has been divided into two periods: active and sleeping. During the active state, the sensor nodes can fulfill the task of transmitting, receiving, and fusing data. During the sleeping state, the sensor nodes turns off their radio model and need not do any task.

As shown in Fig. 3, the operation procedure of EBMA is divided into several rounds. The data gathering in each round starts from the cell with hop N and ends when all data are transmitted to the mobile agent. As described above, the data is transmitted and received only between neighboring cells. When the nodes in the cell complete the data transfer, their states convert from an active state to a sleeping state. Let T_r be the time duration for one round, then each round can be further divided into $t_0, t_1, t_2, \ldots, t_{N-1}$ time-slots for data gathering and a common time T_s for all the nodes in the sleeping state.

As shown in Fig. 7, the time slot of an inter-cluster in EBMA is allocated for each cell. If a hexagon cell does not have any next hop neighboring cell, its time-slot is allocated as 1, then it notifies to its upper hop neighboring cell. If a hexagon cell contains only one next hop neighboring cell, it will set the time-slot distribution the same as its next hop neighboring cell. If a hexagon cell contains more than one next hop neighbor cell, the time-slot of this cell is distributed as the sum of all its next hop neighbor cells.

By introducing time-slot into the multi-hop data gathering, the virtual tree structure is formed as shown in Fig. 8. For cell A and B, so it is assigned two time-slots. Cell E serves as a agent of cell C and D, so it is assigned three time-slots. In this example, the mobile agent informs each cell in its cluster of the time-slots to receive packets from other cells and the time-slots it can use to transmit the packets.

This time-slot allocation can effectively reduce the probability of communication collision, which can save energy. According to the time-slot allocation, we design a state conversion model for intra-cluster nodes as shown in Fig. 9. There are five working states in this model:

- In sleep state, the sensor and communication module of sensor node are both closed, the sensor nodes have no task.
- In fusion state, the sensor and communication module of sensor node is also closed, the sensor nodes fulfill the fusing process.
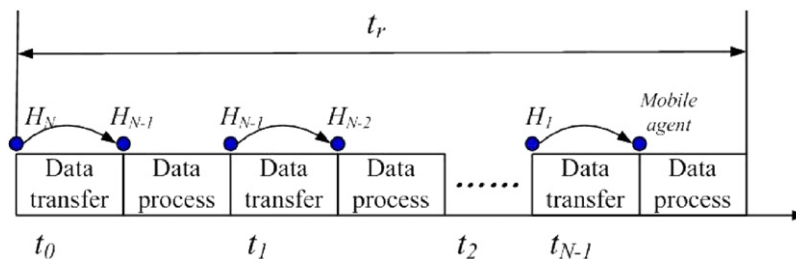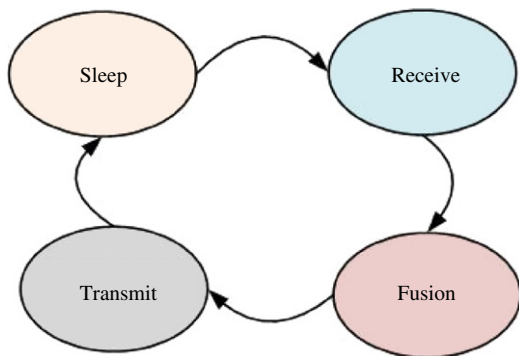

Fig. 7. Operation procedure of EBMA.

Fig. 9. State conversion of sensor node in EBMA.

- In receive state, the sensor module is closed and the communication module is open, the sensor nodes receive data from other nodes.
- In transmit state, the sensor module is closed and the communication module is open, the sensor nodes transmit data to other nodes.

All the working state conversion occurs only at the end of one time-step. The distribution of time-slot make this model simple and easy for the prediction of energy consumption. It is worthy mentioning that in each state, the energy consumption of node is different by various data amounts.

7. Simulation and numerical results

In this section, we evaluate the energy balancing and saving performance provisioning of the proposed EBMA routing. Our experiments are organized as follows. First, we demonstrate the accuracy of the proposed energy prediction scheme with different parameters; Second, we investigate the remaining energy and lifetime of EBMA. Third, we evaluate the performance of EBMA by comparing with a clustering hierarchy based on a cellular topology(CHCT).

7.1. Simulation environment

In all simulations, 300 sensor nodes are uniformly deployed in a hexagon area of $1000 \times 1000m^2$. There are some mobile agents distributed in the hexagon area and only one sink node which is located at the center. The sink node and all mobile agents are not energy limited, while the sensor nodes are all stationary and have the same initial energy 50 J. For the radio model, the parameters are set as follows: $E_{elec} = 50$ nJ/bit, $\varepsilon_{amp} = 0.0013$ pJ/bit/m^4. All simulations are based on a collision-free MAC protocol without data loss. The running time of each round during data gathering is 100 s and each sensor node generates 500 bit data. For ease of reading, the related system parameters are listed in Table 1.

The performance metrics we used in our simulations are accurate in energy prediction and the remaining energy of sensor node, network lifetime and remaining energy ratio. Here, the accuracy of energy prediction reflects the accordance of prediction and real value. The network's lifetime can be measured by the time when the first node exhausts its energy or the network can be declared dead when a certain fraction of nodes die, or even when all nodes die, we define it as the time until the first node dies due to energy depletion for the sake of simplicity. The remaining energy of sensor nodes is the energy remaining when the network's lifetime ends, while the remaining energy ratio is the ratio of remaining energy to the total initial energy.

7.2. Accuracy of energy prediction mechanism

In order to evaluate the accuracy of the proposed energy prediction mechanism, we simulate the operation of the EBMA
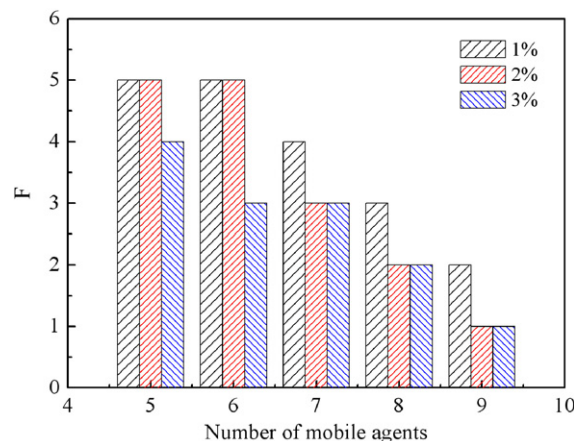

Fig. 10. The number of deviation over the threshold during 100 rounds.
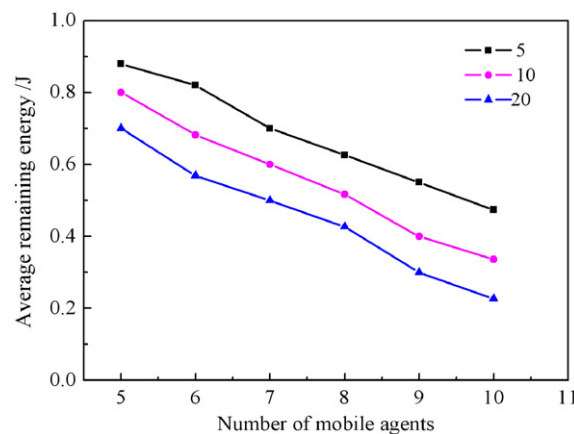

Fig. 11. Average remaining energy with different number of mobile agent2.

routing in many rounds, record the number that the deviation is over the threshold, marked as F. To estimate the energy prediction mechanism, we not only change the set value of the threshold, but also adjust the mobile agent's amount. Fig. 10 shows the time for the deviation over the set value in 100 rounds of EBMA routing with different mobile agent amounts. The value of threshold is set at 1%, 2% and 3%. When the predicted deviation exceeds the threshold, the nodes will recalculate the parameter of energy prediction and make the current actual value as the initial value for the next prediction. It can be seen that the time of deviation over than threshold is not more than 5, which indicates that the value of the predicted result is very close to the actual value. Additionally, the time of deviation exceeding the threshold decreases with an increase of mobile agents. The increase of mobile agents makes the running of sensor nodes become more regular due to a reduction of the hop numbers.

7.3. Remaining energy of sensor nodes and network lifetime

Energy consumption among all sensor nodes is balanced in expectation that they should run out of energy at nearly the same time. The simulations are focused on evaluating the performance of EBMA in terms of energy balancing and network lifetime by recording the time when the sensor nodes are energy exhausted and making a statistic for the remaining energy of other sensor nodes at this time. The effect of network structure on EBMA performance is also considered, by changing the number of agents and hexagon areas, the agent numbers vary from 5 to 10 and the length of hexagons is set as 5 m, 10 m and 20 m, respectively.

Table 1
Parameters in simulation.

Parameter	Value	Parameter	Value
Initial energy	50 J	Network area	1×10^6 m^2
Distribution density	0.003/m^2	Communication bandwidth	1 Mbps
Energy consumption/circuit	50 nJ/bit	Correlation coefficient	0.3
Energy consumption of data slice	10 nJ/bit	Of data fusion	15 nJ/bit
Energy consumption of amplifier	$d <$ 87 m10 pJ/bit m^2	Of amplifier	$d \geq$ 87 m10 pJ/bit m^2

Fig. 12. Effect of q on remaining energy ratio with increasing correlation coefficient.
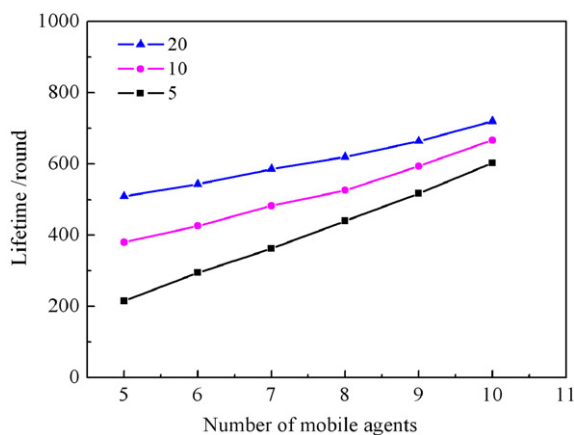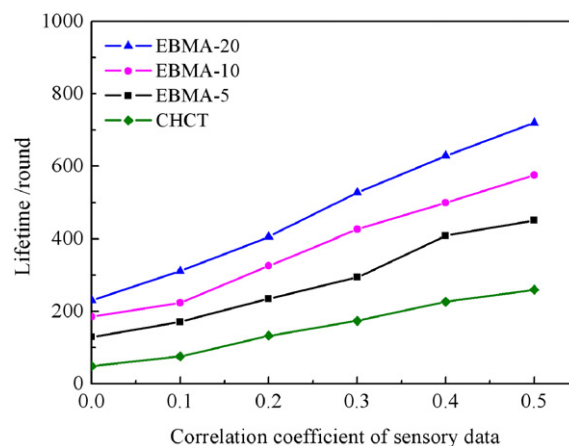

Fig. 13. Effect of q on remaining energy ratio with increasing correlation coefficient.

Fig. 11 shows the average remaining energy of all sensor nodes when the network's lifetime ends. Although the remaining energy is different with the various mobile agent amounts and length of hexagon cells, the maximum value of the remaining energy is not greater than 0.9 J. This is in accordance with our analysis that energy balancing can be achieved by the mobility of agents and all nodes run out of energy at nearly the same time. We notice that the remaining energy decreases with increases in the agent amounts and length of hexagon cells. According to the above analysis, the change will result in the reduction of hops during intra-cluster data gathering, which is of benefit for balancing the energy consumption. Fig. 12 shows the lifetime of the network under different parameters. We observe that the network's lifetime increase with adding more mobile agents. It should be noted that the adding of mobile agent amounts will also increase the price cost of network, while the length of a hexagon cell is limited by real communication.

7.4. Comparison with CHCT routing

In this simulation, we evaluating the performance of EBMA by comparing with a clustering hierarchy based on a cellular topology, which is named CHCT [31]. CHCT adopts the conception of a virtual grid to form the cellular clusters in WSNs, and considers the remaining energy of sensor nodes during the cluster head node selection which has achieved higher performance in energy balancing. EBMA adopts six mobile agents and the length of the hexagon cell is 20 m. Data fusion are both employed in EBMA and CHCT, the effect of data fusion is dependent on the correlation coefficient of generated data. We set the correlation coefficient changes from 0 to 0.5. Fig. 13 illustrates the network's lifetime of EBMA and CHCT with different correlation coefficients. It can be seen that the network's lifetime increases with an increasing correlation coefficient and the lifetime of EBMA is higher than CHCT. The lifetime difference of EBMA and CHCT is also enhanced with increasing correlation coefficient. This is because the increased relativity reduces the extra energy consumption which can strengthen the efficiency of balancing energy consumption in EBMA.

8. Conclusions

For WSNs with a limited energy supply, the unbalanced energy consumption will dramatically reduce the lifetime of the network. In this paper, we theoretically analyze the imbalance of energy consumption when the nodes are uniformly distributed in WSNs. We find that the energy balancing of the whole network is impossible to achieve when multi-hop communication is adopted. Then we investigate the problem of how to achieve energy balancing during data collection in WSNs with mobile agents. We design an energy prediction strategy, which can determine the position of mobile agents to mitigate the uneven energy dissipation problem. Then, EBMA routing is proposed for WSNs where the cluster structure is formed based on a cellular topology with the consideration of the energy balancing of inter-clusters and intra-clusters. Extensive simulations are performed to validate our analysis. Simulation results show that EBMA can effectively balance the energy consumption and performs highly efficiently in large-scale network deployment.

Acknowledgement

References

[1] K. Lin, K. Li, W. Xue, Y. Bi, A clustering hierarchy based on cellular topology for wireless sensor networks, International Journal of Computer Systems Science and Engineering 24 (5) (2009) 345–359.

[2] Y. Yu, B. Krishnamachari, V. Prasanna, Energy-latency tradeoff for data gathering in wireless sensor networks, in: Proc. IEEE INFOCOM'04, Hong Kong, China, 2004, pp. 244–255.

[3] C. Zhao, M. Perillo, W.B. Heinzelman, General network lifetime and cost Models for evaluating sensor network deployment strategies, IEEE Transactions on Mobile Computing 7 (4) (2008) 484–497.

[4] N.A. Pantazis, D.D. Vergados, N.I. Miridakis, D.J. Vergados, Power control schemes in wireless sensor networks for homecare e-health applications, in: 1st International Conference on Pervasive Technologies Related to Assistive Environments, Athens, Greece, 2008, pp. 1100–1107.

[5] A.D. Ahmed, O.K. Mohamed, M. Lewis, On balancing network traffic in path-based multicast communication, Future Generation Computer Systems 22 (2006) 805–811.

[6] H.L. Jason, B. Bobby, Y. Miao, L. Renato, A scalable key management and clustering scheme for wireless ad hoc and sensor networks, Future Generation Computer Systems 24 (2008) 860–869.

[7] O. Powell, P. Leone, J. Rolim, Energy optimal data propagation in wireless sensor networks, Journal of Parallel and Distributed Computing 67 (2007) 302–317.

[8] S. Olariu, I. Stojmenovic, Design guidelindes for maximizing lifetime and avoiding energy holes in sensor networks with uniform distribution and uniform reporting, in: Proceedings of IEEE Conference on Computer Communications, INFOCOM, 2006, pp. 1–12.

[9] X. Wu, G. Chen, Avoiding energy holes in wireless sensor networks with nonuniform node distribution, IEEE Transactions on Parallel and Distributed Systems 19 (5) (2008) 710–720.

[10] H. Zhang, H. Shen, Balancing energy consumption to maximize network lifetime in data-gather sensor networks, IEEE Transactions on Parallel and Distributed Systems 20 (10) (2009) 1526–1539.

[11] B. Krishnamachari, The impact of data aggregation in wireless sensor networks, in: Proceedings of International Workshop on Distributed Event-Based Systems, 2002, pp. 575–578.

[12] P.V. Rickenbach, R. Wattenhofer, Gathering correlated data in sensor networks, in: Proc. ACM Joint Workshop Foundations of Mobile Computing, DIALM-POMC'04, 2004.

[13] A. Goel, K. Munagala, Balancing steiner trees and shortest path trees online, in: Proc. 11th Ann. ACM-SIAM Symp, Discrete Algorithms, SODA'00, 2000.

[14] H. Luo, Y. Liu, S.K. Das, Distributed algorithm for en route aggregation decision in wireless sensor networks, IEEE Transactions on Mobile Computing 8 (1) (2009) 1–13.

[15] A. Anandkumar, W. Meng, T. Lang, A. Swami, Prize-collecting data for cost-performance tradeoff distributed inference, in: IEEE INFOCOM, 2009, pp. 2150–2158.

[16] H. Luo, Y. Liu, S.K. Das, Routing correlated data with fusion cost in wireless sensor networks, IEEE Transactions on Mobile Computing 5 (11) (2006) 1620–1632.

[17] G. Xing, R. Tan, B. Liu, J. Wang, X. Jia, C. Yi, Data fusion improves the coverage of wireless sensor networks, in: International Conference on Mobile Computing and Networking, 2009, pp. 157–168.

[18] R. Liu, G. Rogers, S. Zhou, Honeycomb architecture for energy conversation in wireless sensor networks, in: Proceedings of the 2006 IEEE Global Telecommunications Conference, IEEE, San Francisco, USA, 2006, pp. 1–5.

[19] J. Li, P. Mohapatra, Analytical model and mitigation techniques for the energy hole problems in sensor networks, Pervasive and Mobile Computing 3 (8) (2007) 233–254.

[20] X. Wu, G. Chen, S.K. Das, On the energy hole problem of nonuniform node distribution in wireless sensor networks, in: Proceedings of IEEE International Conference on Mobile Adhoc and Sensor Systems, MASS, 2006, pp. 180–187.

[21] S. Gandham, M. Dawande, R. Prakash, Energy-efficient schemes for wireless sensor networks with multiple mobile base stations, in: Proc. of the IEEE GLOBECOM, IEEE Computer Society, Washington, 2003, pp. 377–381.

[22] Z.M. Wang, S. Basagni, E. Melachrinoudis, C. Petrioli, Exploiting sink mobility for maximizing sensor networks lifetime, in: Proc. of the 38th Hawaii Int'l Conf., IEEE Computer Society, Washington, 2005, pp. 287–295.

[23] R. Shah, S. Roy, S. Jain, W. Brunette, Data mules: modeling a three-tier architecture for sparse sensor networks, in: Proc. of the IEEE Workshop on Sensor Network Protocols and Applications, IEEE Computer Society, Piscataway, 2003, pp. 30–41.

[24] F. Wang, D. Wang, J.C. Liu, Traffic-aware relay node deployment for data collection in wireless sensor networks, in: Proceedings of the 6th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad-HoC Communications and Networks, Rome, Italy, 2009, pp. 351–359.

[25] W.R. Heinzelman, A.P. Chandrakasan, H. Balakrishnan, An application specific protocol architecture for wireless microsensor networks, IEEE Transactions on Wireless Communications 1 (4) (2002) 660–670.

[26] Y. Xu, J. Heide, D. Estrin, Geography-informed energy conservation for ad hoc routing, in: Proceedings of the 7th Annual International Conference on Mobile Computing and Network, ACM, Italy, 2001, pp. 70–84.

[27] X. Wang, T. Berger, Self-organizing redundancy-cellular architecture for wireless sensor networks, in: 2005 IEEE Wireless Communications and Networking Conference, WCNC 2005: Broadband Wireless for the Masses—Ready for Take-off, 2005, pp. 1945–1951.

[28] R. Liu, G. Rogers, S. Zhou, Honeycomb architecture for energy conversation in wireless sensor networks, in: Proceedings of the 2006 IEEE Global Telecommunications Conference, IEEE, San Francisco, USA, 2006, pp. 1–5.

[29] C.Y. Chang, K.P. Shih, S.C. Lee, ZBP: a zone-based broadcasting protocol for wireless sensor networks, in: Proceedings of the 18th IEEE International Conference on Advanced Information Networking and Applications, IEEE, Fukuoka, Japan, 2004, pp. 84–89.

[30] X. Wu, G. Chen, Avoiding energy holes in wireless sensor networks with nonuniform node distribution, IEEE Transactions on Parallel and Distributed Systems 19 (5) (2008) 710–720.

[31] K. Lin, K.Q. Li, W.L. Xue, Y.G. Bi, A clustering hierarchy based on cellular topology for wireless sensor networks, International Journal of Computer Science and Engineering 5 (2009) 51–59.

[32] H. Luo, J. Luo, Y. Liu, S.K. Das, Adaptive data fusion for energy efficient routing in wireless sensor networks, IEEE Transactions on Computers 24 (5) (2009) 345–359.

[33] W.R. Heinzelman, A.P. Chandrakasan, H. Balakrishnan, An application specific protocol architecture for wireless microsensor networks, IEEE Transactions on Wireless Communication 1 (4) (2002) 660–670.

[34] A.F.M. Raquel, A.A.F. Loureiro, B. Nath, Prediction-based energy map for wireless sensor networks, Personal Wireless Communications 2775 (2003) 12–26.

Kai Lin is an assistant professor at the School of Computer Science and Engineering, Dalian University of Technology. He received his B.S. degree in the School of Electronic and Information Engineering, Dalian University of Technology, Dalian, China in 2001, and obtained M.S. and Ph.D. degree from the College of Information Science and Engineering, Northeastern University, Shen yang, China in 2005 and 2008, respectively. His research interests include wireless networks, ubiquitous computing, and embedded technology.

Min Chen was an assistant professor in School of Computer Science and Engineering at Seoul National University (SNU). He was a research associate in Dept. of Computer Science at University of British Columbia (UBC) for half year. He has worked as a Post-Doctoral Fellow in Dept. of Electrical and Computer Engineering at UBC for three years since Mar. 2009. Before joining UBC, he was a Post-Doctoral Fellow at SNU for one and half years. He has published more than 90 technical papers. He is the sole author of a textbook OPNET Network Simulation (Tsinghua Univ. Press, 2004). Dr. Chen received the Best Paper Runner-up Award from The Fifth International Conference on Heterogeneous Networking for Quality, Reliability, Security and Robustness (QShine) 2008. He serves as editor or associate editor for Wiley I. J. of Security and Communication Networks, Journal of Internet Technology, KSII Transactions on Internet and Information Systems, IET Communications, International Journal of Sensor Networks (IJSNet). He is a managing editor for International Journal of Autonomous and Adaptive Communications Systems. He has worked as session chairs in several conferences, such as VTC08, QShine08, ICACT09, Trientcom09, and ICC09. He is a TPC cochair of BodyNets 2010. He is a symposia co-chair and workshop chair of CHINACOM 2010. He is the co-chair of MMASN-09, UBSN-10, and NCAS-11. He was the TPC chair of ASIT-09, ASIT-10, TPC co-chair of PCSI-09, PCSI-10, and UMES-11 publicity co-chair of PICom-09. He serves as the corresponding guest editors for several international journals, such as ACM/Springer Mobile Networks and Applications (MONET), International Journal of Communications System (IJCS). He is an IEEE senior member.

Sherali Zeadally received his Bachelor degree in Computer Science from University of Cambridge, England, and the Doctoral degree in Computer Science from University of Buckingham, England, in 1996. He is an Associate Professor at the University of the District of Columbia. He currently serves on the Editorial Boards of 15 peer-reviewed international journals. He has been serving as a Guest Editor for over a dozen special issues of various peer-reviewed scholarly journals. He is a Fellow of the British Computer Society and a Fellow of the Institution of Engineering Technology, UK. His research interests include computer networks including wired and wireless networks, network and system security, mobile computing, ubiquitous computing, RFID, multimedia, performance evaluation of systems and networks.

Joel J. P. C. Rodrigues is a professor in the Department of Informatics of the University of Beira Interior, Covilhä, Portugal, and a researcher at the Instituto de Telecomunicações, Portugal. He received a Ph.D. degree in informatics engineering, an M.Sc. degree from the University of Beira Interior, and a five-year BS degre (licentiat) in informatics engineering from the University of Coimbra, Portugal. His main research interests include high-speed networks, delay-tolerant networks, sensor networks, e-health, e-learning, and mobile and ubiquitous computing. He is the editor-in-chief of the International Journal on E-Health and Medical Communications. Prof. Rodrigues has served as General Chair, Technical Program Committee Chair, and symposium Chair for many international conferences. He is a member of many international TPCs and several editorial review boards. He has authored or coauthored over 150 technical papers in refereed international journals and conferences, a book, and a patent. He is a licensed professional engineer (as senior member), and he is member of ACM SIGCOMM, a member of the Internet Society, an IARIA fellow, and a senior member of IEEE.