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无线传感器网络中一种层次分簇算法及协作性分析*

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A Hierarchical Clustering Algorithm and Cooperation Analysis for Wireless Sensor Networks

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Abstract: Wireless sensor network combines sensing, computation and communication. Due to limited energy, energy efficiency of sensors is a main concern and a most challenging task for the design of wireless sensor networks. This paper proposes a novel algorithm for network topology, namely Dynamic Energy-Efficient Hierarchical clustering algorithm (DEEH). Different from others, DEEH need to know any local information of sensors. The algorithm can be applied to real large-scale sensor networks in which the sensors have different energy levels and different transmission radius. Compared with the classical clustering algorithm LEACH (Low-Energy Adaptive Clustering Hierarchy), the algorithm is better when the nodes are densely distributed. This paper also considers the selfishness of nodes and analyzes its impact, and introduces a trustful mechanism design that is applied to the algorithm. Under this mechanism, the dominant strategy of selfish nodes is to report their energy truthfully. This strategy can prolong the network lifetime and improve the stability of the network topology.
Key words: wireless sensor network; clustering; hierarchical; selfishness; mechanism design

摘 要: 无线传感器网络是传感技术、计算技术和通信技术的融合.由于传感器节点的能量限制,能量有效性是设计无线传感器网络所关注的一个主要内容,并且已成为一个最大的挑战.提出了一种网络拓扑算法———一种动态、能量有效的层次分簇算法(DEEH).与其他算法不同,该算法无须知道传感器节点的任何本地信息.该算法可应用于更实际的大规模无线传感器网络,如节点具有不同的能量等级、不同的传输半径.将 DEEH 算法与经典的分簇算法 LEACH 相比较,仿真结果表明:当网络节点密度很大时,DEEH 优于 LEACH.同时,还考虑了网络中存在自私节点的情况,并分析了自私节点对网络分簇所带来的影响.在 DEEH 算法中引入机制设计理论,以克服网络中自私节点的影响.实验结果表明:采用机制设计理论,自私节点的占优策略真实地报告它们的能量.这一策略延长了网络的寿命,保证了拓扑结构的稳定性.
关键词: 无线传感器网络;分簇;层次;自私;机制设计
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1 Introduction

Wireless sensor networks have attracted more and more attentions for their wide-range potential applications. Besides military applications, sensor networks can also be used the structural integrity of buildings, home environment, building security and wildlife monitoring, and so on[1,2].

Sensors are capable of monitoring a wide variety of ambient conditions such as temperature, pressure, and motion[3]. Because sensors are powered by batteries, energy-efficient of sensors is a main concern and a most challenging task for the design of wireless sensor networks. In a multi-hop ad hoc sensor network, each node plays the dual role of data originator and data router. A few nodes' malfunctioning can cause serious problems that require rerouting of packets and reorganization of the network. Hence, power conservation and management have additional importance[3]. Recently, many protocols and algorithms about energy-efficiency have been proposed. As reported in Ref.[4], the cluster-based hierarchical model is better than the one-hop or multi-hop model. A recent protocol that optimizes the energy efficiency in sensor networks is Low Energy Adaptive Clustering Hierarchy (LEACH)[5]. LEACH is the architecture that in a fixed area, the uniformly distributed sensor nodes are forming adaptive clusters and rotating cluster head positions randomly to evenly distribute the energy load among the sensors in the network.

Due to the limited energy and other resources, the nodes will represent a feature that maximizes their own benefits, which make them not positively follow the common assumptions. This feature is similar to the auction theory of a generalized second best sealed bid action. Moreover, in adversary environment, there may exist malicious nodes that not only may reject to report their true energy but also may disturb or even destroy the network. We call the character of the former self-interest or selfishness, and the later malice. The selfish character commonly exists in the civil sensor networks, while the malice mainly exists in military networks. In this paper, we only consider the self-interest character of sensor nodes. Due to the self-interest character, the nodes may not report their energy truthfully and forward the relay data actively, that will make the network's topology change frequently. The behavior of selfish nodes can be modeled by game theory and the selfish nodes can be called selfish agents.

To achieve desired properties, most papers assume that nodes cooperate with each other by following the well-defined protocols, regardless of the selfish character of nodes. Inspired by the game theory and mechanism design theory in Ref.[6], we study the selfishly constructed networks by modeling energy report as a mechanism design, and based on the truly reported energy, form the clusters. In this non-cooperative game, we develop such a mechanism that aligns the goals of selfish individual sensors with the global goals of the entire network[7]. In such an approach, sensors within the network are assumed to be rational and nodes making local decisions increase their own utility. The mechanism ensures the global goal and maximum network lifetime when the selfish sensors truthfully report their energy.

2 Related Work

One of the most critical issues in designing sensor network algorithms is to minimize the energy consumption while meeting certain performance requirements such as delay and throughput, etc. Many researchers have focused on issues like energy aware routing[8], energy saving through activation of a limited subset of nodes[9], and proposed protocols and algorithms including energy efficiency[5,10,11].

Clustering in wireless sensor network is a hot topic. A cluster-based routing protocol groups sensor nodes in order to efficiently relay the sensed data to the sink. Each group of sensors has a cluster head that is a specified node being less energy-constrained. Cluster heads aggregate the received data and send them to the sink. Cluster forming is a method that minimizes energy consumption and communication latency. Three most well known hierarchical routing protocols are LEACH, TEEN and Chain-based 3 level PEGASIS[5,10,11]. However, most proposed approaches have too many assumptions on sensor nodes. For example, nodes must have the same initial energy level, nodes are static, or nodes should have much information about other nodes. These assumptions are not practical in reality. Other problems such as in LEACH the cluster head is elected based on a round-robin strategy. This strategy will change the topology of clusters frequently because the selected cluster head may has less energy. Every time, the cluster head changing produces a large overhead since all the nodes in this cluster have to be notified.

Besides, most of the proposed clustering protocols do not consider the selfishness of the nodes. For a practical sensor networks that need utmost cooperation, especially those that are controlled remotely, the selfish nodes will reluctant to tell their private information, such as their own energy. Selfishness in wireless networks is studied only recently. Most approaches fall into two categories: rewarding the cooperative nodes or punishing non-cooperative nodes[12]. Both categories focus on data forwarding strategies between non-cooperation nodes. In the next section we extend the idea to the cluster formation. Our goal is to design an adaptive, energy-efficient, hierarchical cluster formation algorithm that maximizes the lifetime of the sensor networks by selecting the most powerful cluster heads. The selfishness of the sensor nodes is modeled by game theory[13], more specifically, the mechanism design is modeled by designing a game such that selfish behavior of the nodes induces a predictable strategy profile, and the output function for this predicted strategy corresponds to the outcome, called social choice optimum[14]. In other words, the game should be designed in such a way that choosing the predefined strategy that results in the social choice optimum is a dominant strategy for each node[12]. Here dominant means that no node has an incentive to unilaterally deviate from the strategy. If all nodes select a dominant strategy from the strategy profile, then the combination of each node's dominant strategy is called dominant strategy equilibrium. Our goal of mechanism design is to define rules such that the social choice optimum is dominant-strategy equilibrium.

The rest of the paper is organized as follows. Section 3 introduces the basic mechanism design theory. In Section 4, we propose the clustering algorithm without considering the selfishness of nodes, and analyze the compact of selfishness to clustering performance. Then we give the cluster mechanism design strategy that can be applied to our clustering algorithm. In Section 5, we present simulation results about our algorithm with and without the selfish nodes. The results show a better clustering performance can be achieved with our mechanism design strategy for selfish network. In Section 6, we give conclusions.

3 Preliminaries

In this section we introduce some standard notions for mechanism design. We also discuss the dominant strategy implementation in quasi-linear environment described in Ref.[6].

Assume there are n nodes, each node i has its private information $t_i \in T_i$ (termed its type or energy) that maps to the mechanism's output specification $o \in O$, here O is the set of allowed outputs. Each node i has a preference real valued function $v_i(t_i,o)$, called its valuation.

Definition 1. A mechanism $M=(O,P)$ is composed of two elements: An output function $o()$, and an n-tuple of payments $p_1,p_2,\ldots,p_n$. Specifically:

1. The mechanism defines a family of strategies S_i for each node i. Node can choose $s_i \in S_i$ to perform the output function $o(s_1,s_2,\ldots,s_n)$. The mechanism defines a payment $p_i=p_i(s_1,s_2,\ldots,s_n)$ to each node;
2. When the mechanism transfers the payment p_i to node i for the output o, the node's utility will be

$u_i=v_i(t_i,o)+p_i$. This utility* is what the node aims to optimize;

3. We say a mechanism is an implementation with dominant strategies (or in short just an implementation) if for each node i and t_i, there exists a strategy $s_i \in S_i$, called dominant, such that for all possible strategies of the other nodes s_{-i}, s_i maximizes node i's utility. i.e., for every $s_i' \in S_i$, if we define $o=o(s_i,s_{-i})$**, $o'=o(s_i',s_{-i})$, $p_i=p_i(s_i,s_{-i})$, $p_i'=p_i(s_i',s_{-i})$, then $v_i(t_i,o)+p_i \geq v_i(t_i,o')+p_i'$. Then we say for each tuple of dominant strategies $s=(s_1,s_2,\ldots,s_n)$, the output function $o(s)$ satisfies the output specification.

The simplest type of mechanisms is that the nodes' strategies are simply to report their types or energy.

Definition 2. We say that a mechanism is truthful if

1. For all node i, and all t_i, $S_i=T_i$, i.e., the nodes' strategies are to report their true energy. (This is called a direct revelation mechanism);
2. Truth telling is a dominant strategy, i.e., $s_i=t_i$ satisfies the definition of a dominant strategy above.

Definition 3. We say that a mechanism is strongly truthful if truth telling is the only dominant strategy.

The most important implementation of mechanism design is what is usually called the generalized Vickrey-Clarke-Groves (VCG) mechanism (Vickrey (1961)[15]; Clarke (1971)[16]; Groves (1973)[17]).

The VCG mechanism applies to the mechanism design maximization problems where the objective function $g(o,t)$ is simply the sum of all nodes' valuations. The set of possible outputs is assumed to be finite.

Definition 4. A maximization mechanism design problem is called utilitarian if its objective function satisfies $g(o,t)=\sum_i v_i(t_i,o)$.

Definition 5. We say that a direct revelation mechanism $m=(o(t),p(t))$ belongs to the VCG family if

1. $o(t)\in \arg\max_o (\sum_{i=1}^n v_i(t_i,o))$.
2. $p_i(t)=\sum_{j\neq i} v_j(t_j,o(t))+h_i(t_{-i})$, where $h_i()$ is an arbitrary function of t_{-i}.

Theorem (Groves (1973)). A VCG mechanism is truthful.

4 Our Model

We consider a fully dynamic network and all communication between clusters is through cluster heads, satisfying the following assumptions:

(1) The sink node is located in the center of the network;
(2) All nodes in the network have different energy levels and have no location information;
(3) The node's transmission radius is linear to its energy;
(4) Nodes can adjust the power level for transmission and can vary the transmission range;
(5) Links are asymmetric. I.e., node i with higher energy can reach node j that is fall within i's transmission radius, while node j may not reach node i because of its low energy.

We model the wireless sensor network consisting of a set of nodes $N=(n_1,n_2,\ldots,n_i,\ldots)$ that are uniformly distributed in a square area. Nodes share a common wireless channel by using omni-directional antennas.

We divide the large-scale sensor network into clustered layers. All nodes are grouped into clusters. Each cluster votes a cluster head. To save energy and decrease the data redundancy, data should first aggregate in current cluster then be sent to a lower-level cluster head until it reaches the sink node. As data moves from a higher-level to a lower one, it travels greater distances, thus reducing the travel time and latency.

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* Note: This is termed "quasi-linear utility". In this paper, we only discuss this type of utilities.

** Note: s_{-i} denotes $(s_1,\ldots,s_{i-1},s_{i+1},\ldots,s_n)$ and (s_i,s_{-i}) denotes the tuple $(s_1,\ldots,s_n)$.

After initialization of the sensor network, our algorithm forms clusters and chooses one cluster head for each cluster that has the maximum energy level. In order to determine cluster heads, we need a mechanism to reconfigure the clusters. We use the ideas of weighted clustering approach described in Ref.[18].

4.1 Energy model

We assume node i has default energy $P_i^{default}$ that is between $P_{\min}^{default}$ and $P_{\max}^{default}$. When node i sends data, it can choose its transmission power P_i^{tran} (P_i^{tran} maybe less or equal to its default energy) which determines its transmission range. Sine we use omniscient antennas, all the nodes falling within the transmission range can receive the transmission data. If node i appends its transmission power P_i^{tran} to the message header, node j that receives this message can determine the signal strength or the power level at which it receives this message. The relationship between their power levels satisfies[19]

$$P_j^{rec} = \frac{K}{d_{i,j}^{\alpha}} P_i^{tran} \tag{1}$$

where K is a constant, $d_{i,j}$ is the distance between nodes i and j, which is also the communication radius of node i, and α is the distance-power gradient varying between one and six depending on the environment conditions of the network. Our mechanism will ensure the node to report its maximum transmission power when it performs the clustering algorithm. For simplicity, we consider the ideal condition in Eq.(1) that comes K=1, α=2 for the distance-power gradient of the free space.

According to the receiver sensitivity, each node has a minimal receiving power that is the minimal signal strength to receive signals. For simplicity of our algorithm, we assume all nodes have the same receiver sensitivity, thus $P_{i,\min}^{rec} = P_{j,\min}^{rec} = P_{\min}^{rec}$. If node j's minimal receiving power is $P_{j,\min}^{rec}$, to assure j receiving messages from node i, node i's transmission power must be greater than a minimal transmission power $P_{i\to j,\min}^{tran}$. Thus

$$P_{j,\min}^{rec} = \frac{K}{d_{i,j}^{2}} P_{i\to j,\min}^{tran} \tag{2}$$

From Eqs.(1) and (2), we have

$$P_{i\to j,\min}^{tran} = \frac{P_{j,\min}^{rec}}{P_j^{rec}} P_i^{tran} \tag{3}$$

Once node j receives message from node i, it can compute the node i's minimal transmission power by Eq.(3), and it sends back a message to node i to tell the minimal transmission power as well as its default power. This can greatly save node i's energy when it sends data to node j using the minimal transmission power.

4.2 Clustering algorithm with no selfish nodes

A hierarchical clustered sensor network is partitioned to a number of clusters. Node i working as a cluster head is denoted by ch_i. The set of all cluster heads is denoted by CH, $CH \subseteq N$. Current hierarchy cluster heads are denoted by a set of CH_{cur_hier}. All the clusters of the network are denoted by a set of C and current hierarchy clusters are denoted by a set of C_{cur_hier}. The total number of nodes in C_{cur_hier} is denote by $|C_{cur\_hier}|$. We use Γ as a temporary set of stores for current cluster's member nodes. A sensor $j \in \{N-CH\}$ belongs to a cluster c_i if and only if $d_{i,j}$ is minimal among all the cluster heads in CH. The cluster head of c_i is ch_i. It is clear that $|C|=|CH|$. The member of cluster c_i is denoted by M_{c_i}, $\bigcup_{\forall c_i \in C} M_{c_i} = N - CH$.

Now we describe our cluster formation algorithm in detail. The algorithm consists of two stages. In the initial stage the sink node initiates the clustering procedure (Fig.1(a)). Here we assume there always exists neighbors of the sink node. This is reasonable since we consider the nodes to be uniformly distributed. The cluster formation stage can be divided into two similar steps. The first step (Lines 1~8, Fig.1(b)) is the first hierarchy clustering process. The node that has the largest energy will be selected as the cluster head with a higher priority. However there is also an implicit condition that the distance between this node and its current cluster head should be farther than the distance between this node and the cluster head of the up level hierarchy.

1. Sink node broadcasts ***REQ_ENERGY*** (Src, sink, $P_{\rm sink}^{default}$, $P_{\rm sink}^{tran}$; Dst, all) to ask for its neighbors' energy.
2. All nodes that overhear ***REQ_ENERGY*** should report their energy by sending ***REP_ENERGY*** (Src, i, $P_i^{default}$, $P_{i\to {\rm sink},\min}^{tran}$; Dst, sink)
3. $NBR_{sink} \leftarrow \{i$: Sink node received ***REP_ENERGY*** from $i\}$
4. $\Gamma \leftarrow NBR_{sink}$.

(a) Initial clustering procedure

1. while ($\Gamma \neq \Phi$)
2. $ch_i = \max_{i\in\Gamma}\{P_i^{default}\}$
3. $C_{cur\_hier} \leftarrow ch_i$; $CH \leftarrow ch_i$
4. ch_i broadcasts ***REQ_ENERGY***(Src, ch_i, $P_{ch_i}^{default}$, $P_{ch_i}^{tran}$;Dst, all). All nodes overhear ***REQ_ENERGY*** should report their energy ***REP_ENERGY*** **(**Src, j, $P_j^{default}$, $P_{j\to ch_i,\min}^{tran}$; Dst, ch_i), $j\in$ {Neigbors of ch_i}
5. $NBR_{ch_i} \leftarrow \{j$: Current cluster head ch_i received ***REP_ENERGY*** from $j\}$
6. $C_{cur\_hier} \leftarrow c_i$; $C \leftarrow c_i$
7. $M_c = NBR_{ch_i}$; $\Gamma = \Gamma - (M_{c_i} \cap \Gamma)$
8. end-while
9. $N = N - CH_{cur\_hier} - \bigcup_{\forall c_i \in C_{cur\_hier}} M_{c_i}$
10. while ($N \neq \Phi$)
11. $h = |C_{cur\_hier}|$; $\Gamma \leftarrow \{M_{c_i} \mid c_i \in C_{cur\_hier}, i = 1,2,\ldots,h\}$
12. for n_{ch}=1:h
13. $ch_i = \max_{i\in N}\{P_i^{default}\}$
14. $C_{cur\_hier} \leftarrow ch_i$; $CH \leftarrow ch_i$
15. ch_i broadcasts ***REQ_ENERGY*** (Src, ch_i, $P_{ch_i}^{default}$, $P_{ch_i}^{tran}$; Dst, all). All nodes overhear ***REQ_ENERGY*** should report their energy ***REP_ENERGY*** (Src, n_j, $P_j^{default}$, $P_{j\to ch_i,\min}^{tran}$; Dst, ch_i), $j\in$ {Neigbors of ch_i}
16. $NBR_{ch_i} \leftarrow \{j$: Current cluster head ch_i received ***REP_ENERGY*** from $j\}$
17. $C_{cur\_hier} \leftarrow c_i$; $C \leftarrow c_i$
18. $M_{c_i} = NBR_{ch_i}$
19. end-for
20. $N = N - CH_{cur\_hier} - \bigcup_{\forall c_i \in C_{cur\_hier}} M_{c_i}$
21. end-while

(b) Main clustering procedure

Fig.1

When ch_i is selected as a cluster head, it broadcasts ***REQ_ENERGY*** message to all other nodes to indicate its default energy $P_{ch_i}^{default}$ and transmission energy $P_{ch_i}^{tran}$ in the packet header. Each neighbor j of ch_i receiving ***REQ_ENERGY*** can detect the receiving energy P_j^{rec} by the received signal strength indicator (RSSI). According to the transmission energy P_i^{tran} and minimal receiving energy $P_{\min}^{rec}$ of ch_i, neighbor node j can compute its the minimal transmission energy $P_{j\to ch_i,\min}^{tran}$ by Eq.(3). Node j then sends back ***REP_ENERGY*** to ch_i containing its default energy and minimal transmission energy. When ch_i receives ***REP_ENERGY*** from all its neighbors NBR_{ch_i}, the algorithm selects the node with the maximal default energy as the next hierarchy cluster head (Line 13, Fig.1 (b)). Then cluster head ch_i sends clustering message to NBR_{ch_i} to notify the neighbors to join the current cluster c_i.

After clustering finishes, the network is partitioned by some clusters and several hierarchies. Due to the larger energy of the selected cluster heads, the topology can keep stable for a long time. And the transmission power within a cluster can be minimized because the cluster members can send data to their cluster heads using the minimal transmission energy. Since most of the packets are transmitted from cluster members to cluster heads, this greatly saves energy. Thus our clustering algorithm is energy-efficient.

With the nodes sending and receiving data, some of the nodes may be energy-depleted. The network needs reclustering. We design a monitoring process to deal with the reclustering procedure. Different from other topology control protocols such as LEACH[5], which uses an initial percentage of each node to be a cluster head and the clustering is executed circularly, our algorithm is adaptive. The reclustering formation is triggered when needed and it can operate in a local area. When any sensor node detects that its energy is too low to provide service during the network operation, our reclustering process will be triggered and it operates only in the current cluster range. This guarantees the reclustering process takes little time and runs efficiently.

We induce the possible scenarios that may trigger the network reclustering as follows: (i) If a cluster head detects its energy too low to sustain the cluster, it will send its neighbor nodes a message to recluster, and it gives up the cluster head position. All the nodes including the cluster head should individually join other existing clusters or establish a new cluster; (ii) If the cluster head moves out of the current cluster range but within another existing cluster, then it must join the new cluster and be a common sensor node. Nodes within current cluster must reconstruct and define a new cluster; (iii) If a sensor node moves out of the current cluster range but within another cluster range, transfer the sensor node to the later cluster; (iv) If the sensor node moves out of the existing cluster range and is out of range of any other existing cluster, then define a new cluster.

4.3 Mechanism design for selfish network

Previous algorithm is based on the network with honest nodes. However, for a network with selfish nodes, there arises the problem: it may not be the best interest that node i presents its emission signal strength correctly. In reality, for selfish nodes, asserting larger energy will result in a higher payment that the node receives. We discuss the selfishness in a real sensor network and design a mechanism that is fairly enough so that the selfish nodes will not try to cheat. Our goal is to design such a mechanism that causes all nodes to act truthfully, i.e., to reveal their true private information. We design our mechanism design framework as Fig.2 referenced from Ref.[14].

The input of our mechanism is a vector of strategies $s(t)=(s_1,s_2,\ldots,s_n)$ that depend on the true type t. The output function $o=o(s)$ corresponds to a social choice function (SCF),$g(o,s)$. The payment p_i computed by the mechanism is transferred to node i that incents node i to report her*** true energy. In the following, we use the economic mechanism design theory[20] to design the mechanism for selfish network (Fig.2).

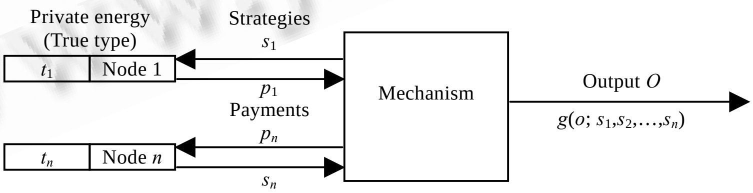

Fig.2 Mechanism design framework

Assume the total cost of topology formation is W. The nodes voluntarily contribute $w_1,w_2,\ldots,w_n$ resources that can be considered as the energy consumed, and w_i is proportional to node i's true energy P_i. Assume nodes benefit

*** It is a tradition in game theory to refer to players as female entities.

from the topology with fixed profits $r_1,r_2,\ldots,r_n$. Once the topology is formed, node i can gain $v_i=r_i-w_i$ net profit or preference value. Thus the necessary and sufficient condition for topology formation is $\sum_{i\in N} v_i > 0$.

Define the objective function $g(o,s)=\sum_i v_i(o,s_i)$. The output space is $O=\{0,1\}$. Each node has an output $o\in O$, representing that the topology has formed or not. The payment that the mechanism transfers to node i is denoted by t_i (t_i may be negative. $t_i<0$ implies the payment is transferred from node i to the mechanism). We then define the quasi-linear utility function of node i that she aims to optimize

$$u_i(o,t_i)=v_i\cdot o+t_i \tag{4}$$

That is to say, whether node i cooperates or not, her objective is to maximize the utility. To ensure the nodes cooperate, we have to maximize their utility. We denote node i's reported preference value by $\hat{v}_i$. Since node i may cheat, $\hat{v}_i$ may not equal to v_i. According to the VCG mechanism, the topology is established when the sum of all nodes' preference values is greater than the sum of all their contributions. Hence

$$o(\hat{v})=\begin{cases}1, & \text{if } \sum_{i\in N}\hat{v}_i>0\\ 0, & \text{if } \sum_{i\in N}\hat{v}_i\le 0\end{cases} \tag{5}$$

Our mechanism must benefit for those who cooperate with others. We associate this benefit with transfer payment t_i for each node. t_i is determined by the following equation

$$t_i(\hat{v})=\begin{cases}\sum_{j\ne i}\hat{v}_j+h_i(\hat{v}_{-i}), & \text{if } \sum_{i\in N}\hat{v}_i>0\\ h_i(\hat{v}_{-i}), & \text{if } \sum_{i\in N}\hat{v}_i\le 0\end{cases} \tag{6}$$

where $h_i()$ is an arbitrary function of $\hat{v}_{-i}$ and is independent of $\hat{v}_i$. Substituting Eq.(5) and Eq.(6) in Eq.(4) with Eq.(5), we have the payoff function

$$p_i(\hat{v})=\begin{cases}v_i+\sum_{j\ne i}\hat{v}_j+h_i(\hat{v}_{-i}), & \text{if } \sum_{i\in N}\hat{v}_i>0\\ h_i(\hat{v}_{-i}), & \text{if } \sum_{i\in N}\hat{v}_i\le 0\end{cases} \tag{7}$$

The selfish node expects to get the transfer payment whatever she cooperate or not. From VCG mechanism, cooperation for a node is a dominant equilibrium strategy. i.e., each node will incentively tell her true energy. We can formulate our results as follows:

Lemma 1. If node i wants to join a cluster, she must tell her true energy P_i.

Lemma 2. If node i hopes the topology not to be formed, she also must tell her true energy P_i.

We omit the proof of these lemmas due to the limitation of space of pages. From the lemmas we see that truth telling is a dominant strategy. Thus we have the following result:

Theorem. Our VCG mechanism is truthful.

To simplify our mechanism, we can define the arbitrary function $h_i()$ as follows

$$h_i(\hat{v}_{-i})=\begin{cases}-\sum_{j\ne i}\hat{v}_j, & \text{if } \sum_{i\in N}v_i>0\\ 0, & \text{if } \sum_{i\in N}v_i\le 0\end{cases}.$$

Then the transfer payment is:

$$t_i(\hat{v})=\begin{cases}-|\sum_{j\ne i}\hat{v}_j|, & \text{if } (\sum_{i\in N}v_i)(\sum_{j\ne i}\hat{v}_j)<0\\ 0, & \text{if } (\sum_{i\in N}v_i)(\sum_{j\ne i}\hat{v}_j)>0\end{cases}.$$

That means the mechanism will punish those whose objective changes the social choice objective. In other words, the mechanism will force the nodes that satisfy $(\sum_{i\in N}\hat{v}_i)(\sum_{j\ne i}\hat{v}_j)<0$ to transfer payment to our mechanism. Because of the selfish feature, no node would like to receive punishment. Then what they can do is to cooperate with their neighbors.

5 Simulation and Evaluation

We simulate a wireless sensor network of 1000 and 2000 nodes using MATLAB. The heterogeneous sensors are uniformly distributed in a 1000×1000 square meters area and the sink node is located in the center of the network. We assign each sensor node a different randomly generated initial energy from 0.3 to 0.5 Joules. A node is considered died if its energy level reaches 0. We also assume that the channel is collision free. In order to measure the energy consumption for collecting sensed data from the cluster members, we used the same energy model introduced in LEACH[5], using radio electronics energy E_{elec}=50*nJ*/bit, radio amplifier energy ε_{amp}=1000*pJ*/bit/m^2 and 512 bit-size sensed data packet.

We simulate the total energy consumed for high-density sensor network when forming the topology. Figure 3 shows our result for 1000-node and 2000-node. The sensor nodes' radio ranges are randomly set from 150m to 300m. And the maximum cluster radius is 300m. From Fig.3, it is clear that the consumed energy for clustering for LEACH increases greatly when the cluster radius increases. However the energy consumed for DEEH increases very slowly. For high-density network, energy consumed for DEEH even does not increase with cluster radius increasing. So DEEH is more suitable for large-scale network.

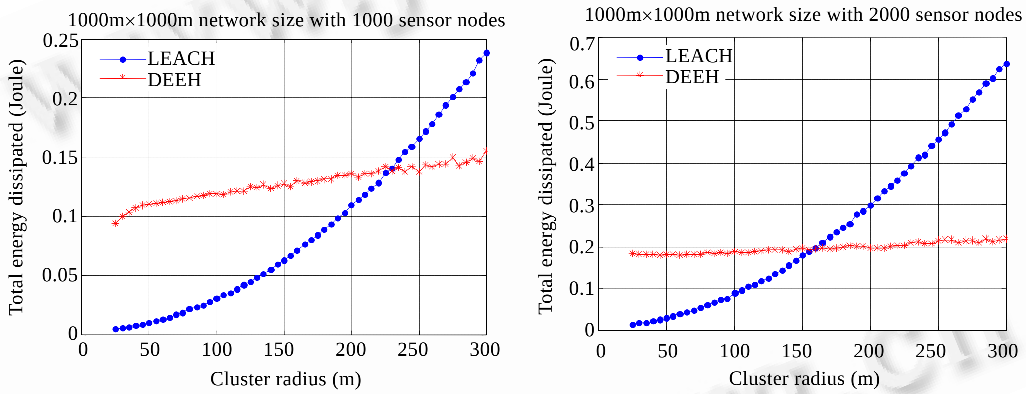

Fig.3 Total energy dissipated of clustering formation for 1000×1000m^2 with 1000 and 2000 nodes

When selfish nodes exist in the network, it is very important to assure the selfish nodes to cooperate and tell their true energy. We simulate the selfish nodes as randomly reporting their local energy from 0 to 0.8 Joules. And we analyze the cluster heads' remaining energy distribution after the clustering procedure ends. Figure 4 shows the simulation results with different selfish nodes in the network.

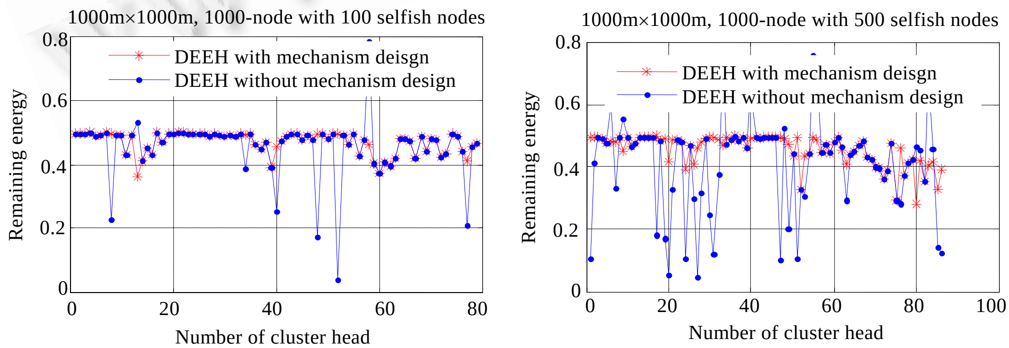

Fig.4 Cluster heads' remaining energy for network with selfish nodes

Because of the selfish nodes in the network, the cluster heads remain energy oscillations greatly. As each node's initial energy is from 0.3 to 0.5 Joules, the remaining energy that is lower than 0.3 or greater than 0.5 can be considered as the declared energy by selfish nodes. The selfish node may underdeclare its energy to save energy or overdeclare to be a cluster head to acquire more benefit from the mechanism. Both of the two declarations can cause the topology unstable. If a node overdeclares its energy and it is elected as cluster head, since its real energy is low, it depletes its energy quickly, and the current cluster must reselect a cluster head. This makes the topology alter frequently. If a node underdeclares its energy, it hardly becomes a cluster head although it has high energy. This will consume the clustering procedure more energy to select the cluster head. From Fig.4, we can see that the selected cluster heads with our mechanism design strategy have relative smooth remaining energy, while if we do not consider the existence of selfish nodes, the cluster heads selected vibrate their remaining energy greatly. The vibration of the remaining energy originates from the nodes' selfish and will cause the topology change frequently, consume more energy, and decrease the network lifetime.

6 Conclusions and Future Work

In this paper, we present a dynamic, energy-efficient hierarchical clustering algorithm for wireless sensor networks. Our algorithm does not assume any knowledge of senor nodes. Our algorithm is dynamic, adaptive and robust. As long as the cluster head has enough energy, the topology is globally stable. We also analyze the selfishness of sensor nodes and provide a dominant strategy that enables each selfish node to report their true local energy. Our algorithm guarantees that most of the selected cluster heads are of less energy constraints. This prolongs the network lifetime and stables the network topology.

Future work should be focused on the distributed mechanism design for the selfish sensor network. Since dominated strategy is a strong constraint for the network, to precisely descript the selfishness of sensor nodes, it is necessary to propose a general design mechanism. Our mechanism only considers the nodes' energy reporting strategy and it omits other cooperating behavior of the nodes. So combining our mechanism with other strategy such as data forwarding strategy and building up a truthful cooperate wireless network are also significant future work.

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