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Energy Optimization and Admission Control Based on Game Theory in Hierarchical Wireless Sensor Networks

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Energy constraint of cluster heads is an important issue in hierarchical wireless sensor networks. This paper proposes a power and admission control scheme based on a non-cooperative game model to solve the problem. By defining a pricing factor in the utility function of cluster head, both the power level and the number of cluster heads can be optimized, while the Nash Equilibrium of the node power is achieved. In order to achieve the equilibrium and validate the decision making process of cluster head, the simulation results are verified by the process when assuming the cluster heads as players.

1. Introduction

The wireless sensor networks (WSNs) consists of a large number of sensor nodes, which have a limited sensing, computing, processing and energy capabilities [1-3]. The applications of WSNs such as intelligent transport system, forest fire monitoring, habitual and environmental monitoring and production control are widely used[4-6]. In these applications, the efficiency of system rather than the single node fairness is emphasized. As the capacity of node battery is limited, the admission control and energy efficiency of sensors is an important issue in minimizing the total energy consumption for life extension in WSNs[7-8]. In hierarchical WSNs (HWSNs), according to the duty and attribute of the sensor nodes, all the nodes are divided into two class: cluster head node(CH) and non-cluster head member node(MN). The cluster head is responsible for scheduling its member nodes to collect sensing information. Moreover, the cluster head will perform data selection and aggregation before retransmits the compressed data to sink node (SN). Generally, the energy consumption of CH is greater than MN.

In order to solve the energy constraint issue of CH, literature [9] proposed a transmitting power algorithm based on data rate to control the transmitting power of nodes in a DS-CDMA system. Literature [10] presented a power control scheme based on the QoS of network to limit the transmitting power of nodes. But, the scheme is too complex to implement in the energy constraint network. In [11], the authors take the signal to interference plus noise ratio (SINR) as the evaluation standard，which determines weather to adopt a new node to the network. As in the same study [11], [12] and [13] use the fairness and reliability of network as the evaluation standard to adjust the transmitting power of nodes. However, the researches in [9-11] assume that sensor nodes exist in an ideal network environment, and only analyses part of nodes behavior. As WSNs is made up of large number of sensor nodes, so it is difficult to reduce the whole network power consumption by using the schemes above.

In HWSNs, the decision making of nodes transmitting power influence each other and the nodes have the incentive to consume its energy solely to maximize its own benefit. Hence, the two network objectives, i.e., the efficiency of power and the reliability of link should be considered simultaneously. To deal with this problem, game theory is an efficient and powerful tool for studying the behavior of players in the game and maximizing the profit of network. Recently, game theory has been widely studied and developed in economy and biology[14-16]. In [17], the authors developed a learning algorithm based on stochastic fictitious play to

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adjust the transmitting power of nodes. The authors in [18] presented an algorithm based on complete information static game to tackle the transmitting power problem in heterogeneous networks. However, the algorithm in [17-18] is complicated. On the basis of different criteria, in literature [19] the author uses a utility function based on node transmitting power to balance the relationship between data quality and node transmitting power. In [20], by applying a pricing scheme in the utility function, the fairness and throughput of network performance are explored. Literature [21] use game-theoretic model to handle the power control problem in multi-source WSNs, in which the sensor nodes can transmit data to multiple clusters. The game-theoretic analysis of node transmitting power is based on the received SINR at the sink node. However, article [19-21] neglected the problem of reliable communication between sink node and cluster head nodes.

The aforementioned design defect brings difficulties in analyzing the behaviors of nodes in wireless sensor network. In this paper, we proposed a power and admission control scheme based on a novel non-cooperative game model to solve the efficiency and reliability problem between the sink node and cluster head nodes. In the game, the cluster head nodes are the players, by formulating a pricing scheme in the definition of node's utility function, the paper analyzes the decision-making process of each node. Then, we present transmitting power algorithm with low complexity to achieve the Nash Equilibrium of the node power. The simulations show that the two network objectives, i.e., efficiency and reliability can be achieved through the game.

The remaining sections of the paper are organized as follows. Section II introduces the system model. In section III the analysis of power and admission control of cluster head nodes will be demonstrated. In section IV we formulate the nodes' transmitting problem formally with the game-theoretic analysis. We also present an algorithm based on the Nash Equilibrium solution in section V. The simulation is included in section VI. Finally, conclusions are drawn in section VII.

2. System model

The notations used in the paper is listed as follows.

Tab. 1. Notations and Definitions

Notation	Definition
CH	Cluster head node
SN	Sink node
MN	Member node
C	Set of cluster head
C_1	Set of active cluster head
C_2	Set of inactive cluster head
N	Number of cluster head
T_i	Number of time slot
P	Transmitting power of cluster head
h	Link gain
λ_i	Receive power value at sink node
γ_i	SINR value of cluster head

In this paper, we focus on the communication problem between cluster head node and sink node. To address the analysis, we assume the following network. We consider a static wireless network, which consist of one sink node and several cluster head nodes. Let N denote the number of the cluster head node and $C=\{CH_i \mid 1\le i\le N\}$ denote the set of cluster head nodes. We use a discrete time model which time is divided into many slots numbered $0,1,2,\cdots$, where each slot is of equal length T. The beginning of one time slot is expressed as t. Using set $C_1(C_1\subseteq C, C_1\neq\varnothing)$ denotes the active CH during one slot and set $C_2(C_2\subseteq C, C_2\neq\varnothing)$ denote the inactive CH. The active CH can transmit data to SN at the beginning of one time slot and the inactive CH can not. During one time slot the number of active CH is stable and the CH will finish decision making, data processing and transmitting. It is worth to note that, when $T_n\left((n-1)T<t<nT\right)$, the number of active nodes may change.

The CH may transmit data to SN simultaneously. A one by one strategy to coordinate the transmissions is ineffective and will lead to bad time delay. That is, if one node is transmitting data to sink node, the others have to wait. In order to avoid the problem above, we use code division multiple access (CDMA) as the network MAC protocol. CDMA scheme not only allow several cluster head nodes transmitting data at the same time, but also has anti-interference properties.

The transmission power of each CH is adjustable. Define P_i as the transmission power of each CH and it's value $p\in[0,p_{\max}]$. When CH_i transmitting data to SN, the receiving power at SN is defined as λ_i, $\lambda_i=p_ih_i$, where h_i is the link gain between CH_i and SN [19]. There exists an additive white Gaussian noise (AWGN) channel between any pair of nodes[22]. In this channel model, the signal to interference plus noise ratio (SINR) can always be used to measure the performance of the link.

The total noise power and interference at sink node, which belongs to cluster head node i is expressed as $\sum_{j\neq i}p_jh_j+\sigma^2$. The SINR at SN achieved by CH_i is defined as[18]

$$\gamma_i=G\frac{p_ih_i}{\sum\limits_{j\neq i}p_jh_j+\sigma^2} \tag{1}$$

where G is processing gain and σ^2 is the thermal noise power at the sink node.

3. Node power and admission control

3.1 Power control

Due to Eq.(1), the CH can obtain a higher SINR level by transmitting data at a high power level. However, in order to achieve a higher transmitting power requires the CH consume more battery power. Moreover, if one of the CH increase its power level, the others will follow. Then a vicious circle is formed until all the CH reach its maximum transmitting power. The result is that every node is facing a worse channel condition. Hence, we develop a power control mechanism to settle this problem. We define that the received power at sink node for cluster head node i should be equal. We can get

$$\lambda_1 = \lambda_2 = \cdots = \lambda_n \tag{2}$$

where $\lambda_i = P_i \times h_i$, (2) can be modified as

$$p_i h_i = h_1 p_1,\ \ i = 1, 2 \ldots, n \tag{3}$$

Substituting Eq.(3) by Eq.(1), we can get

$$\gamma_n = G \frac{p_1 h_1}{(n-1) p_1 h_1 + \sigma^2} \tag{4}$$

Eq.(4) indicates that the cluster head nodes obtain the same SINR value at the sink node.

3.2 Admission control

Based on Eq.(4), with the number and the distance of node increases the SINR decreases. A low SINR lead to a poor performance of the whole network, i.e., when the SINR is too low, SN can not recognize the data send by CH correctly. Therefore, it is useful to drop some nodes whose channels are very bad to improve the performance of the remaining active nodes[20]. This motivates us to define the minimum SINR value which could ensure the quality of transmitting data when transmit from CH to SN. Let γ_{th} denote the threshold. If the SINR for all the nodes is lower than the threshold γ_{th}, those nodes with the poorest link gains are abandoned one by one until the SINR for the remaining nodes becomes equal or higher than γ_{th}. Moreover, threshold γ_{th} is an optimal tradeoff between SINR fairness and capacity of the whole network[11].

As shown in Eq.(5), Γ_i is the SINR obtained by the CH_i to CH_n in which CH_i to CH_n are admitted and CH_1 to CH_{i-1} are abandoned[20].

$$\Gamma_i = G \frac{\lambda_i}{(n-i)\lambda_i + \sigma^2},\ \ i = 1, 2 \ldots n \tag{5}$$

As Eq.(5) satisfies $\Gamma_1 < \Gamma_2 < \cdots < \Gamma_n$ [11], we can drown the conclusion below.

1)If $\Gamma_{th} < \Gamma_1$, all the CH can send data to SN.

2)If $\Gamma_i < \Gamma_{th} < \Gamma_{i+1} (1 \le i \le n)$, CH_1 to CH_n are abandoned and CH_{i+1} to CH_n could send data to SN.

3)If $\Gamma_{th} > \Gamma_n$, all the CH can not send data to SN.

4. Game analysis of node transmitting power

According to Section 3, a higher SINR a node achieves, a lower SINR the other nodes will gain, which implies that the transmitting power decision making process of CH is competitive and interactive. Game theory is an efficient and powerful tool for researching the behavior of players in the game. Hence, in this subsection we develop a non-cooperative game model to analysis the transmitting power decision making process of nodes.

4.1 Non-cooperative game theory model

In general, a game is made up of three elements, a set of players, a set of strategies and a set of utility functions for each player. The strategies of a game can be expressed as $G = \{P_1, P_2, \cdots, P_n; u_1, \cdots, u_n\}$, where n is a set of cluster head nodes. P_i is the strategy space of the nodes. U_i is the utility value of the nodes.

Nash Equilibrium (NE) is a concept that describes the player is assumed to know the equilibrium strategies of the other players, and no player can gain more by changing only its own strategy unilaterally.

If the strategy P_i^* of player i is the best profile among the other strategy P_{-i} in game $G = \{P_1, P_2, \cdots, P_n; u_1, \cdots, u_n\}$, the strategy P_i^* is called strict optimal choice. We have

$$u_i(p_i^*, p_{-i}) > u_i(p_i, p_{-i}),\ \ \forall p_{-i},\ \ \forall i \in N \tag{6}$$

As is shown in Eq.(7), we define ε_i as the best strategy profile of player i. And $E(P) = [\varepsilon_i(P_{-1}), \varepsilon_i(P_{-2}), \ldots, \varepsilon_n(P_{-n})]^T$

is the best strategy profile for all nodes in the game. The best strategy profile is consistent with Nash Equilibrium, so that strategy $\underline{E(P)}$ is a pure-strategy Nash Equilibrium

$$\varepsilon_i(p_{-i}) = \{\arg\max_{p_i \in P_i} u_i(p_i, p_{-i}), p_{-i} \in P_{-i}\} \tag{7}$$

4.2 Game-theoretic analysis of transmitting power

In the game, we assume that the cluster heads are players and the strategy space is the transmitting power and $p \in [0, p_{\max}]$. During the game, the cluster head node will choose a p_i^* to maximize its utility function u_i which is a function of p. The channel capacity utility function which has been used in [20] is suitable for this situation. The utility function is defined as

$$u_i(p_i, p_{-i}) = \log_2(1+\gamma_i), \ \ i \in N \tag{8}$$

In the game, the utility function can be optimized as

$$\max_{p_i \in P_i} \ u_i(p_i, p_{-i}) = \log_2(1+\gamma_i), \ \ i \in N \tag{9}$$

After the initialization of network, the original optimum strategy of each node is transmitting data at their maximum transmitting power which is defined as $P^* = [P_{\max}, P_{\max}, \cdots, P_{\max}]^T$.

Due to the equilibrium, the cluster head node will benefit from transmitting data at its maximum power, but a higher transmitting power lead to a higher interference among the cluster head nodes. Moreover, the reasonable allocation of transmitting power will never be achieved. So a pricing scheme is introduced in the utility function (10) which is considered interference of the cluster head nodes.

$$u_i(p) = \log_2(1+\gamma_i) - q_i, \quad i \in N \tag{10}$$

where q_i is a pricing function of user i for γ_i at the sink node[11].

Unlike the pricing function in [19] is a linear function of transmitting power, the proposed pricing scheme in the paper is a linear function of the SINR. The function of user i is defined as $q_i = \beta_i \gamma_i$, where β_i is the price per unit of the actual SINR at the sink node. Due to the admission control of the cluster head nodes, we know that several nodes will not allow to transmit data to SN. That is, $CH_i(i \in C_1)$ are active and $CH_i(i \in C_2)$ remain inactive. The performance and pricing factor of the two set are different, the SINR of $CH_i(i \in C_1)$ is equivalent to the threshold γ_{th} and $CH_i(i \in C_2)$ is equal to zero. Denote β_{C_1} and β_{C_2} as the pricing factor of $CH_i(i \in C_1)$ and $CH_i(i \in C_2)$[16]. The utility function (10) can be written as

$$u_i(p) = \begin{cases} \log_2(1+\gamma_i) - \beta_{C_1}\gamma_i, \ i \in C_1 \\ \log_2(1+\gamma_i) - \beta_{C_2}\gamma_i, \ i \in C_2 \end{cases} \tag{11}$$

and its equivalent formulation in the game is

$$\max_{p_i \in P_i} \ u_i(p_i, p_{-i}) = \begin{cases} \log_2(1+\gamma_i) - \beta_{C_1}\gamma_i, \ i \in C_1 \\ \log_2(1+\gamma_i) - \beta_{C_2}\gamma_i, \ i \in C_2 \end{cases} \tag{12}$$

4.3 The existence and uniqueness of Nash equilibrium

In this subsection, we will prove the existence and uniqueness of the Nash equilibrium. First, we assume that CH_{k+1} to CH_n can transmit data to SN but CH_1 to CH_k can not, where $k = 1, 2, \cdots, n-1$.

Therefore, $C_1 = \{CH_{k+1}, CH_{k+2}, \cdots, CH_n\}$ and $C_2 = \{CH_1, CH_2, \cdots, CH_k\}$. For each $CH_i \in C_1$, substituting (1) into (11), the first order partial derivative of u_i with respect to P_i is

$$\frac{\partial u_i}{\partial p_i} = \frac{\mathrm{d}u_i}{\mathrm{d}\gamma_i}\frac{\partial \gamma_i}{\partial p_i} = \frac{1}{\ln 2}\frac{Gh_i}{\sum_{j \neq i} h_j p_j + \sigma^2}\left(\frac{1}{1+\gamma_i} - \beta_{C_1}\ln 2\right) \tag{13}$$

For a given threshold γ_{th}, when $\beta_{C_1} = u_i'(\gamma_{th})$, the utility function of $CH_i(i \in C_1)$ reach the maximum value[20]. Set $\beta_{C_1} = \dfrac{\ln 2}{1+\gamma_{th}}$ and (13) can be modified as

$$\frac{\partial u_i}{\partial p_i} = \frac{\mathrm{d}u_i}{\mathrm{d}\gamma_i}\frac{\partial \gamma_i}{\partial p_i} = \frac{1}{\ln 2}\frac{Gh_i}{\sum_{j \neq i} h_j p_j + \sigma^2}\left(\frac{1}{1+\gamma_i} - \frac{1}{1+\gamma_{th}}\right) \tag{14}$$

The CH in set C_1 can transmit data to SN, so $\gamma_i > \gamma_{th}$. We can get $\dfrac{\partial u_i}{\partial P_i} < 0$, the u_i is a decreasing function of P_i. Hence, the best transmitting power strategy of the nodes in set C_1

is $P_i = 0$. Putting $P_i = 0$ into (1), $\gamma_i = 0$ can be computed, which contradicts the assumption $\gamma_i > \gamma_{th}$. So the assumption is not satisfy this kind of situation. The $\gamma_i \le \gamma_{th}$ is valid and $\frac{\partial u_i}{\partial P_i} \ge 0$ can be derived. Therefore, $\frac{du_i}{d\gamma_i} \ge 0$. We can draw the conclusion that $\arg\max_{p_i \in P_i} u_i$ and $\arg\max_{p_i \in P_i} \gamma_i$ is equivalent. because of $\gamma_i \le \gamma_{th}$, we have $\arg\max_{p_i \in P_i} \gamma_i = \gamma_{th}$. Putting it into (15)

$$p_i = \frac{\sigma^2}{1 - \sum_{j=k+1}^{n} \frac{\gamma_i}{\gamma_j + G}} \frac{\gamma_i}{h_i(\gamma_i + G)} \tag{15}$$

we can get

$$\arg\max_{p_i \in P_i} u_i = \arg\max_{p_i \in P_i} \gamma_i = \frac{\gamma_{th}\sigma^2}{h_i[G - (n-k-1)\gamma_{th}]} \tag{16}$$

where $\arg\max_{p_i \in P_i} u_i$ is the best transmitting power strategy of the nodes in set C_1

For each $CH_i \in C_2$, putting (1) into (11), the first order partial derivative of u_i with respect to P_i is

$$\frac{\partial u_i}{\partial p_i} = \frac{\mathrm{d}u_i}{\mathrm{d}\gamma_i}\frac{\partial \gamma_i}{\partial p_i} = \frac{1}{\ln 2}\frac{Gh_i}{\sum_{j \ne i} h_j p_j + \sigma^2}\left(\frac{1}{1+\gamma_i} - \beta_{C_2}\ln 2\right) \tag{17}$$

For a given threshold γ_{th}, when $\beta_{C_2} \ge u_i'(0)$, the utility function of $CH_i(i \in C_2)$ reach the maximum value[20]. Set $\beta_{C_2} = 1/\ln 2$ and (17) can be rewritten as

$$\frac{\partial u_i}{\partial p_i} = \frac{\mathrm{d}u_i}{\mathrm{d}\gamma_i}\frac{\partial \gamma_i}{\partial p_i} = \frac{1}{\ln 2}\frac{Gh_i}{\sum_{j \ne i} h_j p_j + \sigma^2}\left(\frac{1}{1+\gamma_i} - 1\right) \tag{18}$$

Since $\gamma_i \ge 0$, so we can get $\frac{\partial u_i}{\partial P_i} \le 0$, the u_i is a decreasing function of P_i. Therefore, the maximum value of u_i will be achieve when $P_i = 0$. That means $P_i = 0$ is the best strategy profile for the nodes except CH_i. At last the best response strategy for set C is

$$E(p) = \left[\underbrace{0, 0, \ldots, 0}_{k}, \frac{\gamma_{th}\sigma^2}{h_i[G - (n-k-1)\gamma_{th}]}\right]^{\mathrm{T}} \tag{19}$$

Therefore, we can conclude that $E(p)$ is proven to be a Nash equilibrium of the game.

Proposition 1 The Nash equilibrium $E(p)$ is unique.

Proof We assume another Nash equilibrium exists besides $E(p)$. By the definition of Nash equilibrium, we can get $u_i\left(P_i', P_{-i}'\right) \ge u_i\left(\varepsilon\left(P_{-i}\right), P_{-i}'\right)$. For $CH_i(i \in C_1)$, the u_i is a increasing function of P_i, so $P_i' \ge \varepsilon\left(P_i\right)$ can be drawn. But it conflicts with $\varepsilon_i(p_{-i}) = \arg\max_{p_i \in P_i} u_i$. For $CH_i(i \in C_2)$, the u_i is a decreasing function of P_i, it can be deduced that $P_i' \le \varepsilon\left(P_i\right) = 0$. But it conflicts with $P_i' \ge 0$. To all the above, we can deduce another Nash equilibrium except for $E(p)$ does not exist. Hence, the Nash equilibrium $E(p)$ is unique.

5. Algorithm

In this section, we introduce a low complexity algorithm based on game-theoretic analysis to compute the best transmitting power of cluster heads. The process of the algorithm is shown as follows:

Set the initial transmitting power vector $p \in [0, p_{\max}]$. Let l denote the iteration number of the system, $N\left(l\right)$ denote the active cluster head number in iteration l. we also define the best transmitting power strategy of the nodes as

$$\Omega_i(l) = \frac{\gamma_{th}\sigma^2}{h_i[G - (N(l)-1)\gamma_{th}]} \tag{20}$$

Step 1 After the network is initialized, $CH_i(i \in C)$ chose a transmitting power ranging from 0 to $P_{\max}$. The iteration $l = 0$.

Step 2 $CH_i(i \in C_1)$ upload its link gain h_i to SN at the beginning of iteration l. SN computes the minimum value of all upload h_i and the active number of cluster head. Then SN send the $h_{\min}$ and the number of active cluster head to all the cluster head nodes.

Step 3 All the active CH update their transmitting power.

Step 4 If $h_i = h_{\min}(l)$ and $\Gamma_i \le \gamma_{th}$, let $P_i(l+1)=0$, then go to Step 2. If $h_i = h_{\min}(l)$ and $\Gamma_i > \gamma_{th}$, let $P_i(l+1)=\min(P_{\max},\Omega_i(l+1))$. Then go to Step 2.

Else if $h_i \ne h_{\min}(l)$ and $\Omega_i(l)>0$, let $P_i(l+1)=\min(P_{\max},\Omega_i(l+1))$. Then go to Step 2. Otherwise let $P_i(l+1)=P_{\max}$. Then go to Step 2.

The flow chart of the algorithm is indicated in Fig.1.

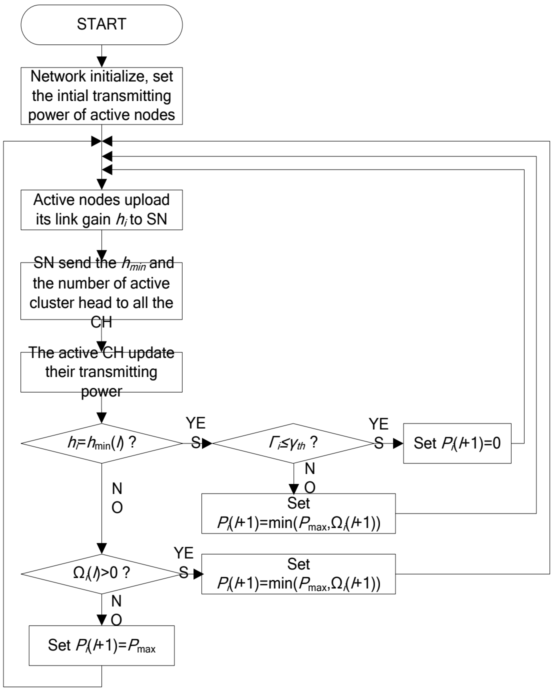

Fig. 1 The flow chart of algorithm

In the algorithm, SN gathers the link gains which send by the active CH and computes the minimum of all link gains and the number of active CH. After the computation, SN sends back both values to all active nodes. If one cluster head node decided transmitting power is greater than zero during iteration l, it begin to transmit data to SN; if not, it remains inactive. The information that CH requires in one iteration is the minimum value of link gain and the number of active CH send by SN.

Proposition 2 For $\forall P$, the iterations to converge to the Nash Equilibrium is within the number of the cluster head nodes.

Proof we assume that the link gain of CH_1 satisfies $h_1 = h_{\min}(0)$ at the beginning of each iteration. If $\Gamma_1 = \gamma_{th}$, $G-(N(l)-1)\gamma_{th}>0$ can be denoted, which means $\Omega_i(0)>0$. Hence, all the CH go back to step 2 and $P_i(1)=\min(P_{\max},\Omega_i(1))$. So $h_{\min}(1)$ and the number of active nodes equal to those at iteration $l=0$. The situation of the following iterations is the same as iteration $l=0$. If $\Gamma_1 < \gamma_{th}$, $P_l(1)=0$ can be denote, CH_1 stop transmitting data to SN. In iteration 2, the other CH can transmitting data to SN and $P_i(2)=\min(P_{\max},\Omega_i(2))$, $P_i \ne 0$, $i \ne 1$. What is more, we can get $h_2 = h_{\min}(2)$ and the number of active node is $N-1$. In the same way, if $\Gamma_2 \ge \gamma_{th}$, all the active CH go back to step 2 except CH_1. Otherwise, CH_2 stop transmitting data. We can draw the same conclusion that one CH with the poorest link gain should determine whether to stay active or not during one iteration. Hence, the worst situation is that the algorithm will not converge until the iteration equals to N.

6. Numerical Results

The hierarchical network topology is illustrated in Fig.2. We consider a network with one single sink node and ten cluster heads. Ten nodes randomly deployed and the distance vector is

$$d=[50,45,40,35,26,23,21,19,16]$$

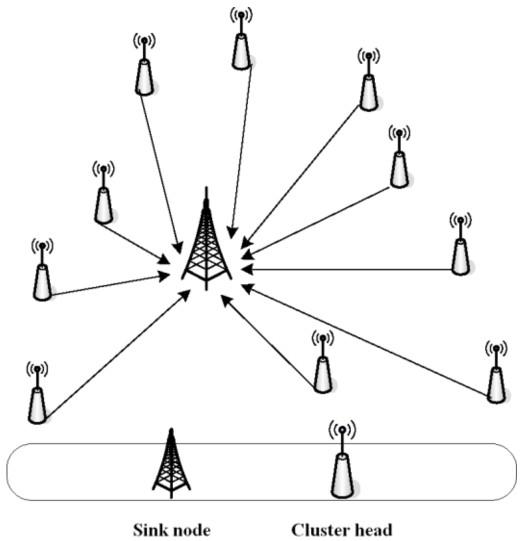

Fig. 2 The hierarchical network topology

The threshold of SINR γ_{th} is 18 dB. The other parameters are listed in Table 1.What's more, the link gain is defined by $h_i = v \times d_i^{-4}$, where v is a channel fading factor and d is the distance between CH and SN.

Tab. 2. Simulation Parameter

Parameter	Value
N, number of active cluster heads	10
G, processing gain	100
σ^2, AWGN power at SN	5×10^{-15}Watts
P, maximum transmition power	0.1mWatts
d, maximum transmition range	50meter

A Simulation of admission control

In Fig.3, we show a comparison of SINR value in (dB) of three different methods: (1) Using game theory without admission control. (2) Transmitting data at maximum power. (3) Using game theory under admission control.

In [19,22], we know that the transmitting power of each CH is reduced by using game theory without admission control. However, the SINR is at a low level in the presence of a high number of nodes. As Fig.3 shows, all the ten nodes' SINR value are below the threshold 18 dB, that means, the quality of the transmitting data can not be guaranteed when transmit data to SN. By comparing with the scenario in which admission control is adopted, we can see that six active nodes can transmit data to SN and the data quality can be guaranteed simultaneously. That is, the network performance is improved by adopting admission control scheme in transmitting data from CH to SN.

As discussed in Section 2.2, in the scenario that admission control is not used, the Nash Equilibrium of CH transmitting power is transmitting data at their maximum power, i.e., [0.1,0.1,…,0.1]mW. As illustrated in Fig. 3,

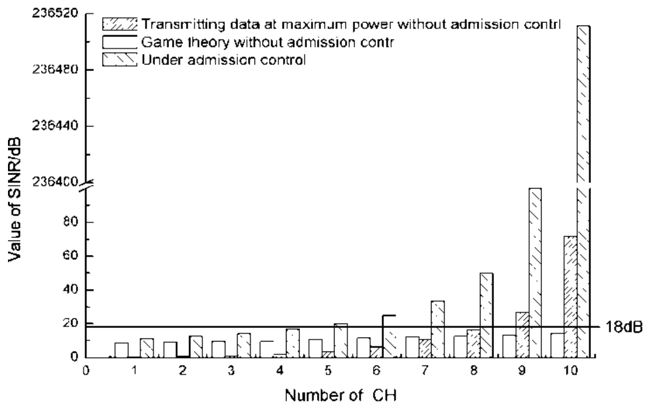

Fig. 3 Comparison of SINR value of three different methods.

only CH_9 and CH_{10} satisfy the SINR threshold, indicating that the other eight nodes are stop transmitting data. Only 20% of the nodes can transmit data to SN. What's worse, all the CH are working at their maximum transmission power which cause a huge energy consumption in the energy constraint network.

When admission control is adopted in the network, as it is shown in Fig. 3, CH_1 to CH_4, which possess Γ_i below the SINR threshold, can not transmit data to SN. On the other hand, CH_5 to CH_{10}, which possess Γ_i greater than the SINR threshold, can transmit data to SN and the quality of data can be ensured as well.

B Simulation of game-theoretic power algorithm

Fig. 4 shows the transmitting power versus each iteration. In Fig.4, transmitting power of CH_1 to CH_4 converge to zero at iterations 1 to 4. During the iterations, CH_5 to CH_{10} are retaining at maximum transmitting power. At iteration 5, the transmitting power of CH_5 to CH_{10} converges to far lower than the maximum value. The values of the transmitting power and SINR are shown in Table III.

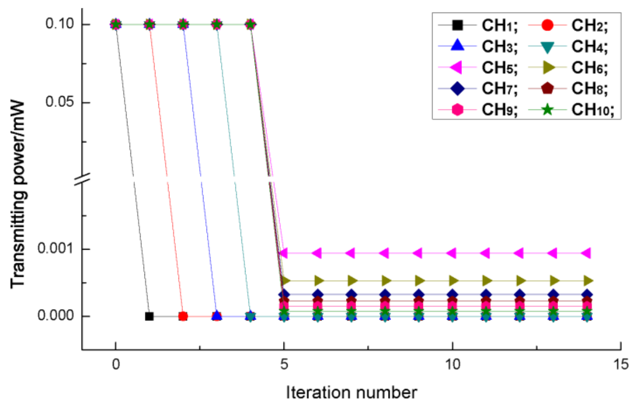

Fig. 4 Transmitting power of nodes in each iteration

Tab. 3. Transmitting power and SINR value

Node number	Transmitting power/10^{-4}mW	SINR/dB
CH_1	0	11.062
CH_2	0	12.459
CH_3	0	14.252
CH_4	0	16.64
CH_5	9.406 45	19.979
CH_6	5.306 82	24.982
CH_7	3.249 77	33.313
CH_8	2.258 49	49.969
CH_9	1.513 41	99.916
CH_{10}	0.761 06	236 511.2

The original transmitting power versus Nash Equilibrium transmitting power is illustrated in figure 5. We can see that the transmitting power of CH_5 to CH_{10} converges to far lower than the maximum value. The reason for the optimization is that, with the adopting of admission control scheme, the channel condition is improved, moreover, by introducing game theory in analyzing the nodes behavior, the node can transmit data at a lower power.

Fig. 6 depicts the SINR versus the iteration numbers. With the increase of the iteration number, the SINR of CH_1 to CH_4 become to zero one by one. However, at iteration 6 the SINR of CH_5 to CH_{10} are 18dB. Combine Fig. 4 and Fig. 6, we can come to a point that the node power level is decreased and the data quality is improved by using game-theoretic approach in analyzing the transmitting power of active cluster nodes. The point to reduce energy consumption of network is also achieved.

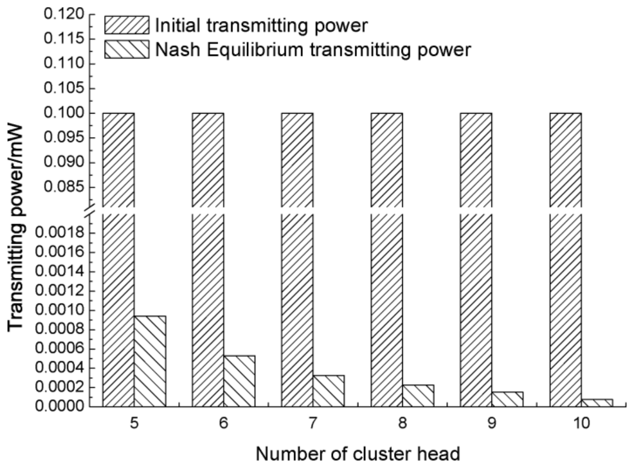

Fig. 5 Nash Equilibrium transmitting power vs. original transmitting power

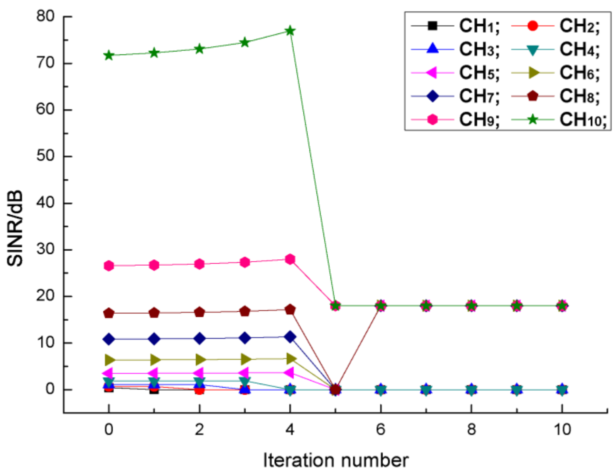

Fig. 6 SINR value of nodes in each iteration

C The number of cluster head versus γ_{th}

Fig. 7 shows the number of cluster head versus SINR threshold γ_{th}. As the SINR threshold increases, the number of active cluster head nodes decreases. When $\gamma_{th} \leq 10\text{dB}$, all the nodes can transmit data to SN. However, there is only one node can transmit data to SN when $\gamma_{th} \geq 100\text{dB}$. Hence, we can satisfy different capacity of the network by changing the value of γ_{th}.

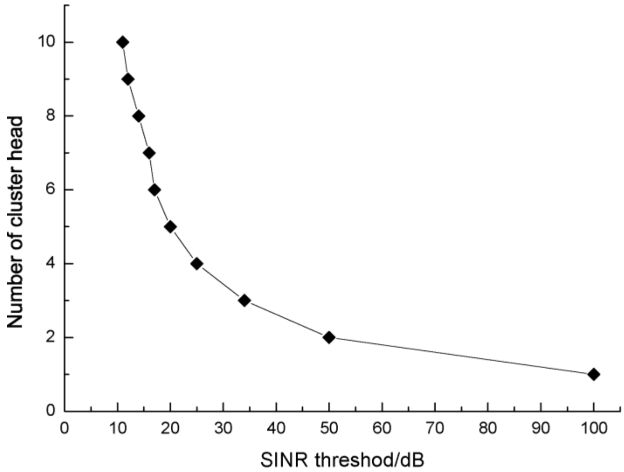

Fig. 7 Number of remain CH vs. SINR threshold

7. Conclusion

In this paper, we propose a power and admission control scheme based on a novel non-cooperative game model in hierarchical wireless sensor networks. In the scheme, the two network objectives, i.e., the efficiency and reliability are considered simultaneously. We formulate the optimal transmitting power problem as a non-cooperative game. In the game, the cluster head nodes are designed as the players, by formulating a pricing scheme in the definition of node utility function, the paper analyzes the decision-making process of each node. Based on the game-theoretic analysis, we present a low complexity transmitting power algorithm to achieve the Nash Equilibrium and proved the uniqueness of the Nash Equilibrium. The simulation shows that both the power efficiency and link reliability are improved. Our future work is considering more than two levels in HWSNs.

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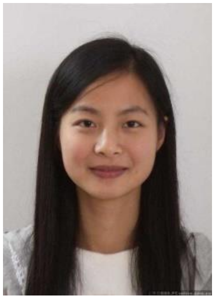

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