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Non-cooperative Game based Social Welfare Maximizing Bandwidth Allocation in WSNs

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***Abstract*—In this paper, we deal with possible data transmission congestion on the sink node in wireless sensor networks (WSNs). We consider a scenario in which all the sensor nodes have a certain amount of storage space and acquire data from the surroundings at heterogeneous speed. Because receiving bandwidth of the sink node is limited, a proper bandwidth allocation mechanism should be implemented to avoid possible congestion or data loss due to the overflow of some sensor nodes. To address this problem, we firstly design a novel bandwidth allocation mechanism, SWM, that can maximize the social utility, an indicator of every sensor node's satisfaction degree and the social fairness. Furthermore, we model the allocation process under the SWM as a noncooperative game and figure out the unique Nash Equilibrium. The uniqueness of the equilibrium demonstrates that this network will actually approach to a fair and stable state.**

I. Introduction

With the on-going development of wireless sensor networks (WSNs), it is anticipated that we can acquire information about any corner of the world instantly. Thousands of collaborative sensors provide a promising future for many monitoring, surveillance and control applications [1]. WSNs are deployed by a large number of sensor nodes and a few sink nodes [2]. Because the limited power capacity of the sensor nodes [3], the routing is typically on a multi-hop basis [4] as shown in Figure 1. Many work has been proposed to solve the problems in WSNs including connectivity [5], mobility [6] and congestion avoidance [7] and diagnosis [8].

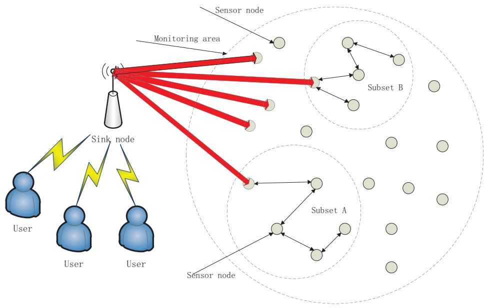

Fig. 1. The model of WSN

In WSNs, congestion not only leads to packet loss but also causes extra-power consumption, which sharply reduces the life time of WSNs. The congestion can be divided into two types: node-level congestion, which indicates the buffer overflow of nodes, or link-level congestion, which indicates the collision of different nodes accessing the same channel. The node-level congestion can be further divided into two kinds: sensor nodes congestion and sink node congestion. Extensive work has been done to address the node-level congestion. In [7], Silva analyzed the congestion model of randomly distributed sensor nodes. In [9], Liu presented a congestion control mechanism based on extended DCCP protocol. In [10], Wang utilized the cross-layer optimization to form a priority based congestion control method. The previous works mainly dealt with the congestion among sensor nodes and ignored the congestion on sink node. In fact, sink nodes are the most crucial part of WSNs because all the information in a given area will be transmitted to it. As shown in Figure 1, one side of the sink node links to the users and the other side of sink node links to the terminal nodes of the ad hoc sensor networks. However, the transmission bandwidth of the sink nodes is limited and therefore, the many-to-one transmission (red lines in figure 1) can lead to devastating congestion. Tang [11] illustrated the bottle neck effect of sink nodes in his paper and proposed physical layer solution. The traditional multi-access bandwidth allocation mechanisms[12] cannot be implemented in WSNs because of the limited memory and computation capability of sensor nodes. Therefore, the saturation rates of the sensors' storage should be take into consider.

In our paper, we propose non-cooperative game based bandwidth allocation mechanism considering the saturation rates and the demands of sensors as well. The sensors can bid for the bandwidth they require and the sink node will implement social-welfare maximizing (SWM) resource allocation algorithm to allocate bandwidth to sensors. We model the bidding process of sensors as a noncooperative game. By strict game theoretical analysis, we find that this bidding game has a unique Nash Equilibrium solution. Moreover, we will show that by bidding the equilibrium solution, the network can achieve social fairness and approximately the same saturation rates so that congestion and data loss is avoided to the best.

This paper is organized as follows: In section II, we describe the problem in detail and present the model of the network; in section III, we illustrate our social-welfare-maximizing bandwidth allocation mechanism; in section IV, we model the process of bandwidth competition as a non-cooperative game and deduce the unique Nash Equilibrium of this game; in section V, we set up three simulations to show the proposed

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characters of our congestion-avoiding mechanism. Finally, we conclude in section VI.

II. Problem Formulation and System Model

In our WSNs protocol, there are multiple sensor nodes and only one sink node. The receiving data flow of different sensor nodes varies because most of the sensors work in an event-driven way. The heterogenous sensing rates require the sensor nodes to have a certain amount of storage capacity, which acts as a temporary buffer of the spike sensing data flow. However, the capacity of the buffer is limited so that a fare bandwidth allocation mechanism is needed to prevent possible data overflow.

Assume there are N sensor nodes. The sensor node set is defined as $\mathcal{P} = \{P_1, \cdots, P_N\}$. The sink node has a limited receiving bandwidth B_S. Also, we introduce the parameter *data saturation rate*, S_i^M, to denote the ratio between the amount of data storage to the total data storage capacity of sensor node i in M^{th} time slot.

Definition 1(Data saturation rate): Given the data storage capacity Ω_i for sensor node i, its amount of data storage Ω_{i0} at the beginning of the 1^{st} time slot and the data transmission time T_{Tr}, in each time slot, the *data saturation rate* of sensor node i in M^{th} time slot is:

$$S_i^M = \frac{\Omega_{i0} + M \cdot \Delta\Omega_i - \sum_{t=i}^{M}(\omega_i^t \cdot T_{Tr})}{\Omega_i} \qquad \forall P_i \in \mathcal{P} \tag{1}$$

To simplify our notation, in rest of our paper, we discard the superscript M and assume that all our discussions are carried out in an arbitrary M^{th} time slot. Hence, the saturation rate vector is $\mathbf{S} = \{S_1, \cdots, S_N\}$, which we assume is known to the central sink node.

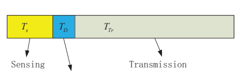

Fig. 2. A illustrate of one time slot

From figure 2, we can readily figure out that the time slot in our model is divided into three parts.

- **Sensing period:**All sensor nodes simultaneously monitor their adjacent environment for T_S and store the sensed information. For any arbitrary sensor node i, this process causes an increase, $\Delta\Omega_i$ of its data storage.
- **Decision period**
  This period lasts for T_D and starts with all the sensor nodes sending their *bidding messages* to the central sink node. Then, based on the bidding messages and data saturation rates of all sensor nodes the central sink node utilizes our *SWM* algorithm to calculate the bandwidth allocation $\mathbf{W} = \{\omega_1, \cdots, \omega_N\}$ whose aim is to maximize the *social utility*.
- **Transmission period**
  Any arbitrary sensor node i transmits its data to the central sink node for time T_{Tr} with the allocated bandwidth ω_i indicated by the bandwidth allocation vector **W**.

Definition 2(Bidding message):We use b_i to denote the *bidding message* of sensor node i and $\mathbf{b} = \{b_1, \cdots, b_N\}$ the bidding message vector.

It is necessary to point out that in our theoretic game framework sensor nodes are allowed to freely choose their bidding messages in order to maximize their own benefits.

Definition 3(Utility of each sensor node):The *utility function* of sensor node i in an arbitrary M^{th} time slot is defined as:

$$U_i(\omega_i) = \log(\frac{\omega_i}{b_i} + 1) \qquad \forall P_i \in \mathcal{P} \tag{2}$$

We are enlightened by [13] to give this utility function because this utility function have the following properties:1.Definition 3 depends entirely on the ratio between ω_i and b_i, so it can reflect the degree of satisfaction of each sensor node in any time slot;2.$U_i(0) = 0$;3. $U_i(\omega_i)$ is concave.

Definition 4(Social utility):The *social utility* in our wireless sensor networks, which represents the social satisfaction degree is defined as follows:

$$\sum_{i=1}^{N} S_i \log(\frac{\omega_i}{b_i} + 1) \tag{3}$$

(O1): Bandwidth allocation **W** should be the solution of the following constraint maximization problem:

$$max \sum_{i=1}^{N} S_i \log(\frac{\omega_i}{b_i} + 1) \qquad s.t. \sum_{i=1}^{N} \omega_i \leq B_S \qquad \forall P_i \in \mathcal{P}, 0 \leq \omega_i \leq b_i \tag{4}$$

III. Social-Welfare-Maximizing(SWM) Bandwidth Allocation Algorithm

In this section, we provide the bandwidth allocation algorithm that maximizes social welfare based on **b** and S.

A. Contents and Explanations of SWM Algorithm

As is proposed in algorithm 1, our SWM algorithm takes the bidding message vector **b** together with the saturation rate vector **S** as inputs and outputs the bandwidth allocation vector **W**. We will prove in the following subsection that **W** resulted from this algorithm is in fact the solution of the maximization problem **O1**.

In fact, the SWM algorithm can be regarded as an enhanced version of progressive water-filling procedure. That is, any arbitrary sensor node i can be viewed as a container with depth $\frac{b_i}{S_i}$ and width S_i. Furthermore, the height of the bottom of any of these containers are the same as its depth. The area of the water that ends up in the container represents the bandwidth resource allocated to that particular sensor node. Now that the area of the container is b_i for sensor node i in M^{th} time slot, its allocated bandwidth will definitively be no larger than b_i. During the process of the SWM algorithm, water is firstly filled into the containers whose bottoms have a relatively low

Algorithm 1: Social-Welfare-Maximizing Bandwidth Allocation Algorithm

Input: Bidding message vector **b**, saturation rate vector S
Output: Bandwidth allocation vector **W**
1: If $\sum_{i=1}^{N} b_i \leq B_S$, return $\mathbf{W} = \mathbf{b}$;
2: Run sorting algorithm $\mathcal{A}$ on $\mathcal{P}$.
Let $\mathcal{P}^{'}$ be the resulted sensor node set with $\frac{b_i}{S_i}$ in an ascending order and $i^{'} = \boldsymbol{f}(i)$ the mapping of their indices from $\mathcal{P}$ to $\mathcal{P}^{'}$.
3: In set $\mathcal{P}^{'}$, we carry out step 4 to step 15.
4: Initialize $\mathcal{L} = \frac{b_1}{S_1}$; $m = 1$; $n = 2$; $\mathcal{S} = S_1$; $\mathcal{C} = B_S$;
5: **while**($\mathcal{C} > 0$)
6: **if**($(\min\{\frac{b_n}{S_n}, \frac{2b_m}{S_m}\} - \mathcal{L}) \cdot \mathcal{S} \geq \mathcal{C}$)
7: $\mathcal{L} += \frac{\mathcal{C}}{\mathcal{S}}$; $\mathcal{C} = 0$;
8: **else if** ($\frac{2b_m}{S_m} < \frac{b_n}{S_n}$)
9: $\mathcal{C} -= (\frac{2b_m}{S_m} - \mathcal{L}) \cdot \mathcal{S}$; $\mathcal{L} = \frac{2b_m}{S_m}$; $\mathcal{S} -= S_m$; $m++$;
10: **else**
11: $\mathcal{C} -= (\frac{b_n}{S_n} - \mathcal{L}) \cdot \mathcal{S}$; $\mathcal{L} = \frac{b_n}{S_n}$; $\mathcal{S} += S_n$; $n++$;
12: **end if**
13: **end if**
13: **for** $i^{'} = 1 : N$
14: $\omega_{i^{'}} = \min\{max\{S_{i^{'}} \cdot (\mathcal{L} - \frac{b_{i^{'}}}{S_{i^{'}}}), 0\}, b_{i^{'}}\}$;
15: **end for**
16: Utilize indices mapping $\boldsymbol{f}$ to obtain ω_i from $\omega_{i^{'}}$.
17: Return **W**

height. As long as a specific container is full, no water will be poured into this container any longer. Moreover, one inherent requirement of this water filling procedure is to ensure that the containers that are neither empty nor full should have the same water level(relative to the common ground). Finally, after all resource B_S has been depleted or bandwidth requirement from all sensor nodes satisfied, this algorithm terminates .

B. Characters and Computational Complexity of SWM Algorithm

In subsection B we prove and characterize the SWM Algorithm.

Theorem 1: The SWM algorithm resolves the following maximization problem (3) described in section II.

Proof:The substantiation of theorem 1 is demonstrated in the technical report of our paper.

Theorem 2: The bandwidth allocation **W** resulted from the SWM algorithm is *Pareto Optimal*.

Proof: From the proposed SWM algorithm, we can readily deduce that this algorithm terminates in two cases.

- $\sum_{i=1}^{N} b_i \leq B_S$
  In this scenario, all sensor nodes all completely satisfied.
- $\sum_{i=1}^{N} b_i \leq B_S$ and the bandwidth resource B_S is completely utilized. Under such circumstance, for any other resource allocation, the increase of any sensor node's utility will necessarily result in decrease of other nodes' utilities.

Thus, for the resulted allocation **W** of the SWM algorithm, without a reduction of at least one sensor node's utility, it is impossible to improve the utility of other nodes. Hence, **W** is Pareto optimal.

Theorem 3: The SWM algorithm ensures the following condition:

$$\frac{S_i}{b_i} \geq \frac{S_j}{b_j} \Rightarrow U_i(\omega_i) \geq U_j(\omega_j), \forall P_i, P_j \in \mathcal{P} \tag{5}$$

Proof: As defined in equation (2), the utility of sensor node i in time slot T is $U_i(\omega_i) = \log(\frac{\omega_i}{b_i} + 1)$. Moreover, based on the SWM algorithm, if the condition $\frac{S_i}{b_i} \geq \frac{S_j}{b_j}$ holds, the height of the bottoms of containers i and container j satisfies the condition $\frac{b_i}{S_i} \leq \frac{b_j}{S_j}$. Thus, final water level in container i will necessarily be lower than that in container j. That is, $\frac{b_i+\omega_i}{S_i} \leq \frac{b_j+\omega_j}{S_j}$. Then, two cases exist.

- $\frac{b_i+\omega_i}{S_i} = \frac{b_j+\omega_j}{S_j}$
  Divide $\frac{b_i}{S_i} \leq \frac{b_j}{S_j}$ by $\frac{b_i+\omega_i}{S_i} = \frac{b_j+\omega_j}{S_j}$, we get $\frac{\omega_i+b_i}{b_i} \geq \frac{\omega_j+b_j}{b_j}$. Thus, $U_i(\omega_i) \geq U_j(\omega_j)$ is substantiated.
- $\frac{b_i+\omega_i}{S_i} < \frac{b_j+\omega_j}{S_j}$
  Then, container i is full after running the SWM algorithm, indicating $\omega_i = b_i$. Hence, $U_i(\omega_i) = \log 2$, which is the largest possible value for the utility of any individual sensor node. As a result, the condition $U_i(\omega_i) \geq U_j(\omega_j)$ also holds true.

Remarks: Theorem 3 presents some major features of the SWM algorithm. It illuminates that sensor nodes whose saturation rate to bidding message ratio are relatively larger enjoy higher utility. On one hand, it renders sensor nodes with a higher data saturation rate, or equivalently stronger transmission inclination, larger bandwidth. On the other hand, sensor nodes who seek to send in excessively large bidding messages will be punished for less bandwidth allocation, or even no allocated bandwidth at all given that their bids are sufficiently large. This is because even if the sink node allocates all of its bandwidth resource to such a sensor node, the social degree of satisfaction will still be rather unpromising.

Theorem 4:The computational complexity of SWM is $\Theta(N)$.

*Proof:*In SWM, we utilize a sorting algorithm $\mathcal{A}$ to derive a sorted set of sensor nodes $\mathcal{P}^{'}$. However, we do not delve into the selection of a specific algorithm $\mathcal{A}$ in this paper. The only constraint on $\mathcal{A}$ is that its running time should be $\Theta(N)$ or approximately $\Theta(N)$. Such an algorithm $\mathcal{A}$ could be *Counting Sort algorithm, Radix Sort algorithm* or *Bucket Sort algorithm* [14]. More importantly, we need to notice that apart from the sorting procedure, the rest of algorithm 1 is linear because it only takes to go over all nodes for once to finish the allocation and can be finished within time $\Theta(N)$. Therefore, algorithm 1 can be regarded as a linear time programme.

IV. Noncooperative Game Analysis for Sensor Nodes' Strategies

As we have seen from the previous section, when receiving the bids of the sensor nodes, the sink node can implement the SWM algorithm to allocate the transmission bandwidth so as to achieve maximal social welfare. In the analysis of SWM, we assume that the sensor nodes all submit their maximum requirements of transmission bandwidth to the sink node. In reality, the truthful bids may not the most beneficial bids for the sensor nodes. The SNs can freely choose their bidding strategy and this decision process can be modeled as a noncooperative game. We will examine the property of this game and prove that this game will converge to the unique Nash Equilibrium solution.

We model the proposed mechanism as a complete information noncooperative game. That is to say the utility function of each node is in the same form and the saturation rate vector $\mathbf{S} = \{S_1, \cdots, S_N\}$ is common knowledge to all participants. Then we present the definition of the noncooperative game.

Definition 5: The non-cooperative game is defined as follows:

The player set: $\mathcal{P} = \{P_1, \cdots, P_N\}$.

The strategy space $\mathbf{b} = \{b_1, ..., b_n\}$ $b_i \in R^+$.

The utility of P_i positively correlates to the bandwidth allocated to the sensor node.

Lemma 1: The mapping function defined by the SWM: $\mathbf{b} \rightarrow \mathbf{W}$ is quasi-concave.

Proof: For the convenience of analysis, we denote the strategy profile as $\mathbf{b} = \{b_i, \mathbf{b}_{-i}\}$ where $\mathbf{b}_{-i}$ is the fixed bids of players other than P_i. Let's consider the case b_i gradually increases from zero. As illustrated in the previous section, because the bottom and the area of the container are both small. The $\omega_i(b_i)$ allocated by SWM will increase monotonically. However, when the bid increases to a certain level, the allocated bandwidth starts to decrease monotonically with bid b_i until $\omega_i(b_i) = 0$. This property guarantees that the upper-level contour set is convex so that the function is quasi-concave.

Theorem 5 This noncooperative game has at leat one Nash Equilibrium solution.

Proof: Lemma 1 shows that our game protocol fits the generalized Nash Equilibrium existence condition[15] proposed by Debreu, Glicksberg and Fan in 1952. Therefore, there is at least one Nash Equilibrium in this game.

Lemma 2: For any player $P_i \in \mathcal{P}$, the strategy $\hat{b_i} = \frac{B_s S_i}{\sum_{j=1}^{N} S_j}$ will generate the result of $\hat{\omega_i} = \frac{B_s S_i}{\sum_{j=1}^{N} S_j}$.

Proof: Assume the total resource can give the P_i the bandwidth of $\omega_i = \frac{B_s S_i}{\sum_{j=1}^{N} S_j}$. This means that the water level of SWM mechanism is at height $h = \frac{2\hat{b_i}}{S_i} = \frac{2B_s}{\sum_{j=1}^{N} S_j}$. Any other players say P_j may report its strategy by b_j' in two different ways:

- **When** $b_j' \leq \frac{B_s S_j}{\sum_{j=1}^{N} S_j}$: We have $\frac{2b_j'}{S_j} \leq \frac{2B_s}{\sum_{j=1}^{N} S_j} = h$. Hence, $\omega_j' = b_j' \leq \frac{B_s S_j}{\sum_{j=1}^{N} S_j}$.
- **When** $b_j' \geq \frac{B_s S_j}{\sum_{j=1}^{N} S_j}$: we have $\frac{b_j'}{S_j} \geq \frac{B_s}{\sum_{j=1}^{N} S_j} = h$. So $\omega_j' = (h - b_j'/S_j)S_j \leq \frac{B_s S_j}{\sum_{j=1}^{N} S_j}$.

Furthermore, we notice that $B' = \sum_{i=1}^{N} \omega_i' \leq \sum_{i=1}^{N} \frac{B_s S_i}{\sum_{j=1}^{N} S_j}$. Therefore, if the sensor bids $\hat{b_i} = \frac{B_s S_i}{\sum_{j=1}^{N} S_j}$, the amount of bandwidth resource it will receive will be the same as it has asked for.

Theorem 6: The strategy profile $\hat{b_i} = \frac{B_s S_i}{\sum_{j=1}^{N} S_j}$ where $i = 1, ..., N$, is a Nash equilibrium.

*Proof:*As we have proved in lemma 2, under this strategy profile, any sensor can achieve the bandwidth of $\omega_i = \frac{B_s S_i}{\sum_{j=1}^{N} S_j}$ regardless of other sensors' strategies. Therefore, no one can further improve its utility because $\omega_i \leq B_s - \sum_{k \neq i} \hat{b_k} = \hat{b_i}$.

Theorem 7: The Nash equilibrium solution $\hat{b_i} = \frac{B_s S_i}{\sum_{j=1}^{N} S_j}$ where $i = 1, ..., N$ is the unique Nash equilibrium.

Proof: Assume there is another Nash Equilibrium $\tilde{b_i}, \tilde{x_i}$. From the analysis of SWM mechanism we can see that if $\tilde{b_i} \leq \hat{b_i}$, the final assignment of bandwidth $\tilde{\omega_i}$ will be less that $\hat{\omega_i}$. Therefore, the $\tilde{b_i}$ should be larger than $\hat{b_i}$.

Moreover, because the $\hat{\omega_i}$ cannot be further improved, we have $\tilde{\omega_i} = \hat{\omega_i}$ for all sensor nodes. Therefore, the final water height and the initial position of the bottoms should both be the same among different containers. That is to say, $\tilde{b_i}$ can only be in the form of $\tilde{b_i} = (1+\delta)\hat{b_i}$ for all sensor nodes. However, this strategy profile is not an equilibrium because any node can slightly reduce its bid and gain an extra allocation.

V. Simulation

In this section, we consider a practical WSNs with 200 sensor nodes and only one sink node. A single time slot in our model lasts for 1 second and in the 40th time slot, each sensor node experiences a random sudden increase in the amount of information it senses due to abrupt changes in its monitoring environment. Also, we assume that each sensor node has a homogeneous local storage capacity of $\Omega_i = 10MB$, the bandwidth limit of the central sink node is 3MB/s and the increase of the amount of the sensed information is the average bandwidth resource allocated in this network multipied by 0.9.

In figure 3, we demonstrate that by utilizing the SWM algorithm defined in section III the social utility can be maximized. Specifically, we compare the resulted social utility of the SWN algorithm with the case when we allocate bandwidth resource proportional to sensor nodes' bidding messages that is $\omega_i = \frac{b_i B_S}{\sum_{j=1}^{N} b_j}$. The horizontal axis represents the change in the total bandwidth resource of the sink node. We assume that the initial bandwidth of the system is 1MB/s and it is doubled at the beginning of every time slot. Notice that in figure 3, the resulted social utility by the SWM algorithm is always larger than the case of allocating the bandwidth resource according to $\omega_i = \frac{b_i B_S}{\sum_{j=1}^{N} b_j}$.

In figure 4, the horizontal axis represents the time since we start to analyze the WSNs and the vertical axis is the data saturation rates of sensor nodes. For purpose of simplification, we only choose to draw the curves of five of the sensor nodes in our WSNs. Notice that although different from the beginning, data saturation rates of senor nodes gradually approach to the same value as the accumulation of time. In the 40th time slot, all sensor nodes experience a sudden increase in their data storage and after 180s sensor nodes' data saturation rates tend to be the same again.

In figure 5, we represent a comparison between the initial data saturation rates of all sensor nodes with the resulted data saturation rates at the time of 180s in figure 4. From figure 5, we notice that the initial data saturation rates are heterogeneous among different sensor nodes and at the time of 180s all sensor nodes share approximately the same data saturation rate.

VI. Conclusion and Future Work

In this paper, we propose the conception of data saturation rate of a single sensor node. Based on the bidding messages and data saturation rates of all sensor nodes, the sink node

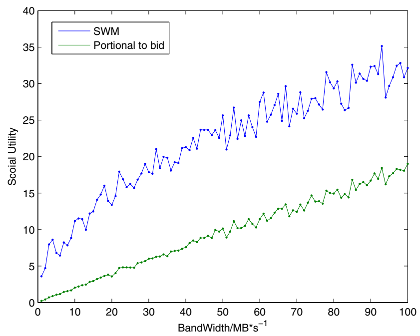

Fig. 3. The comparison of social utility

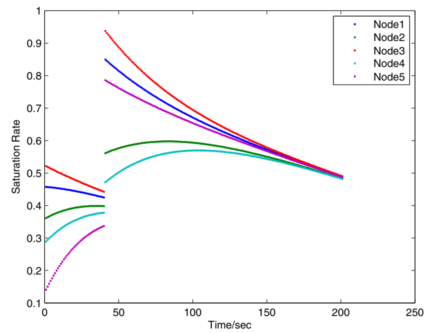

Fig. 4. The saturation rate variation of five different sensor nodes

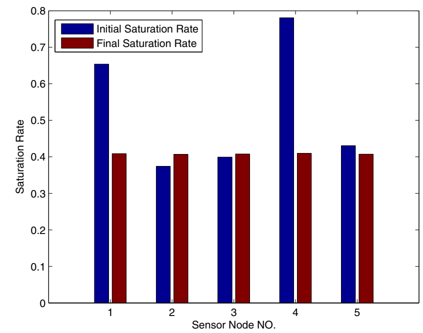

Fig. 5. The contrast between saturation rate in the start and the end of the simulation period

calculates the allocation of its bandwidth to the sensor nodes in our WSNs by using our SWM algorithm to achieve maximal social utility. Also, bandwidth allocation resulted from this algorithm satisfies the condition that sensor nodes with a larger saturation rate to bidding message ratio will be guaranteed a larger utility. As proved in section III, such a bandwidth allocation is a Pareto optimal as well.

In addition, we formulate our model as a non-cooperative game structure. In our theoretic non-cooperative game analysis, we also have proved that there is a unique Nash Equilibrium of this game and the Equilibrium strategy for each sensor node is to send bids to the central sink node following the relationship $\omega_i = \frac{S_i B_S}{\sum_{j=1}^{N} S_j}$. Notice in our simulation that if sensor nodes send their bids according to their Equilibrium strategies, after a sufficiently long period of time, regardless of the initial distribution of sensor nodes' distribution rates, sensor nodes will have approximately the same data saturation rates. The salient feature of our bandwidth allocation mechanism indicates that our WSNs have the ability to cope with the situation when one or more sensor nodes experience a spike.

In our paper, we assume that all the sensor nodes know others' saturation rates. Therefore, without the knowledge of others' saturation rates, the sensors may not choose the Nash Equilibrium as their bids. Our future work will alternate the game structure to a dynamic game and hope to use a distributed mechanism to make the sensors gradually converge to the equilibrium point. Furthermore, we may use mature spectrum managing mechanisms from cognitive radios [16] [17] [18].

VII. Acknowledgment

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