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Discussions on Data Aggregation in Wireless Sensor Networks

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Abstract: For energy saving of sensor networks due to power restriction, the data aggregation technique has been proposed. In this paper, we discuss the trade off between communication delay and energy consumption of the technique. For the tandem sensor networks the analytic results as well as simulation results shows that although for the power saving the full aggregation where all data are aggregated is effective, the delay is very large compared with non-aggregation method when a sensing event occurs sparsely in time. Based on the results, to suppress the delay, this paper proposes two partial aggregation methods. One is called RP (random partial aggregation) where some waiting data randomly can be transmitted to the lower node without the sensing data arrival according to the random pushing rate. When the rate equals to zero, the method is equivalent to full data aggregation, while it is non-aggregation when the rate is infinite. The other technique is more sophisticated method called WRP (waterfalls RP). In WRP, each node has its independent random pushing rate. Farther nodes from the sink have larger random pushing rate to suppress the delay. The nodes nearer the sink have less rates and tend to achieve aggregation to suppress the congestion around the sink. The simulation results show the efficiency of WRP.

無線センサーネットワークにおけるデータ集約に関する考察

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概要：データ集約は無線センサーネットワークにおいてデータ量を削減する方法として注目されている。データ量削減により消費電力を抑えられるものの遅延が大きくなる。本稿では、データ集約方式の遅延と消費電力のトレードオフ関係を議論する。まず、CSMA を前提としてデータ集約を行う方式と行わない方式をマルコフ解析とシミュレーションによってその特性を明らかにする。その後、部分的に集約するRP(Random Push)方式と WRP(Water falls RP)を提案する。RP では配信の遅延を抑えるためにランダムに選択されたパケットを集約せずに送信する方式である。WRP は RP を一般化したものであり、ノード毎に非集約パケットの選択確率を変える方式である。特に、シンクから遠いノードでは低い確率で集約して遅延を軽減し、シンクに近づくほど高い確率で集約を行いシンク付近の輻輳を避ける。RP および WRP をマルコフ解析およびシミュレーションによって評価し、その有効性を論じる。

1. Introduction

In recent years, sensor networks attract significant attention due to its applicability to many fields for effective collection of sensing data with less cost. Generally, a sensor network consists of sensor nodes equipped with sensors, processors and wireless transceivers and sinks which are attached to the Internet. A sensor node observes an event by its sensors, generates a digital event data, and transmits the data by the transceiver to the adjacent node. By multi-hopping, the sensed data reach the sink via which users at somewhere in Internet can observe those events. Due to the restriction on battery capacity, power saving of nodes is important issue. Among techniques of power-saving of nodes is the data aggregation as well as routing protocols and MAC protocols. In this paper, we focus on the data aggregation.

PEGASIS [2] is one of data aggregation techniques. In PEGASIS a sensor node combines the event data and the received data from the upper adjacent node, and transmits to the lower adjacent node. A leader node finally transmits aggregation data to sink. It proposes transmission scheduling, where the farthest node from the sink transmits data first to an adjacent node. On the other hand, Data Aggregation[3],[4] and Directed Diffusion[5] are other well-known schemes of data aggregations. Data Aggregation forms a cluster of some sensor nodes and gathers data to the cluster head, and it proposes a communicating method between cluster heads. LEACH[6], HEED[7], CLUDDA [8] are protocols also to collect data with cluster architecture.

In this paper, at first, we analyze communication delay and energy consumption of the full aggregation compared with non-data aggregation with Markovian chain and simulation. The results show the trade off between delay and power consumption of data aggregation. When the network is low loaded, full aggregation is appropriate for power consumption, but it suffers large delay. Then, based on the results, a novel technique called RP (random pushing)[1] is discussed, which can control delay with single parameter, random pushing rate. This paper also proposes more sophisticated method called WRP (waterfalls RP). In WRP, farther nodes from the sink have larger random pushing rate. The simulation results show the efficiency of WRP.

In section 2, we describe the tandem sensor network model and define some terminology. Section 3 analyzes the delay and power consumption of full data

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aggregation as well as non-data aggregation in a tandem sensor network. Section 4 provides basic performance evaluations of specific parameters all of which are from practical protocols, such as Zigbee, CSMA/CA, and DSR. The evaluation is also done by simulations. After the discussion of the basic evaluation of full data aggregation and in section 5, partial aggregation methods, RP and WRP are proposed and evaluated.

2. Target Sensor Network

2.1 Model

In this paper, we use a tandem network as shown in Fig.1. The reason of the simple model is that it enables us to analytic model, that it is the most basic model of sensor networks. The results can be extensible to more complex topology. For example, in the tree topology sensor network, the load of nodes is larger near the sink. As we state in the later section, WRP can incorporate individual node load for data aggregation.

Sensor node transmits its sensing data to the sink. If sensor nodes cannot transmit data to the sink directly, i.e., with one hop, data are transmitted with multi-hopping via intermediate nodes to the sink.

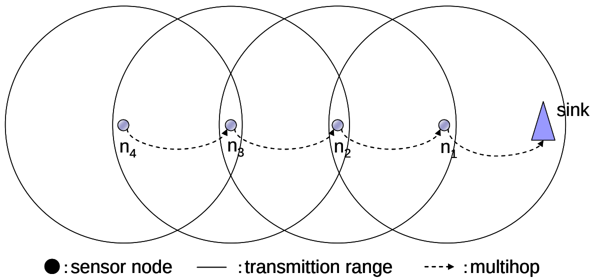

Fig.1 Tandem sensor networks.

2.2 Definitions

- n_i denotes the i-th node from the sink. N is a set of all nodes.
- n_{i+1} is called the adjacent upper node of n_i, while n_{i-1} is the adjacent lower node of n_i. A set of nodes of $\{n_k \mid n_k \in N, k > i\}$ denotes the upper nodes of n_i, while $\{n_k \mid n_k \in N, k < i\}$ denotes the lower nodes of n_i.
- E_{ij} denotes the j-th event at node n_i.
- D_{ij} denotes the sensed data which generated by observing E_{ij}. The data size of D_{ij} is identical and fixed to all nodes.
- Data transmission time $\tau^1(i)$ is defined as a time interval between the instance that a data is transmitted from n_i and the instance that the data is received at the adjacent lower node n_{i+1}.
- E_{ij} may occur at an arbitrary time. Therefore, if E_{ij} occurs during transmitting some data of n_i to n_{i-1}, E_{ij} has to wait to be transmitted to avoid collision. This time is called in this paper backoff time. $\tau^c(i)$ is defined as a time interval between the instance that E_{ij} occurred and the instance that the n_i starts to transmit D_{ij}.
- Total delay T(i) shows a time interval between the instance that E_{ij} occurred at n_i and the instance that the sink receives D_{ij}.
- Suffices imi and agg attached to $\tau^1(i)$ and $\tau^c(i)$ mean non-aggregation and aggregation, respectively.
- CSMA is assumed for medium access control.
- The transmission range of each sensor nodes is assumed d[m].
- If n_i uses data aggregation, when it receives data from n_{i+1}, it waits for the data arrival of D_{ij}. After D_{ij} arrived, n_i combines D_{ij} and the received data from n_{i+1}. The size of the combined data can be $A_f (\geq 1)$ times larger than the size of D_{ij}. A_f is called aggregation factor.
- The propagation delay between adjacent nodes is assumed to be negligible.

2.3 Non-aggregation

Fig.2 shows the sequence chart of non-aggregation data transmission. In this model, when a data generates at a node, it immediately transmits the data to the adjacent lower node without data aggregation.

In Fig. 2, after E11 occurs n5 sends D11 to the adjacent lower node n4. During transmitting D11, n5 exchanges data and ACK with n4. CSMA/CA makes some data deferred for transmission. For example, after E31 is observed D31 has to wait to be transmitted until n3, n2 and n1 complete the transmission of D41 to avoid the

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collisions on links between n3 and n2, and n2 and n1.

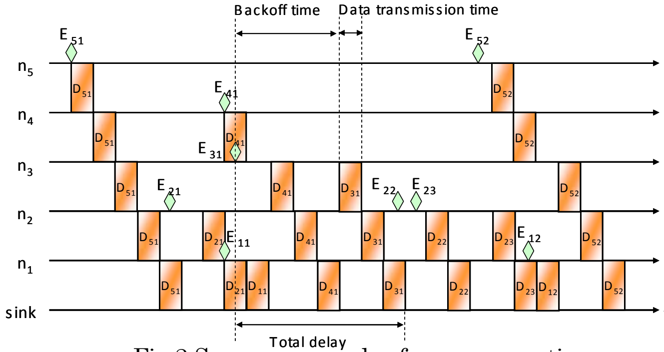

Fig.2 Sequence sample of non-aggregation.

2.4 Full aggregation

Fig. 3 shows the sequence chart of data aggregation. In this model, when a new data arrives at a node, the node transmits the data. If a node receives data from its adjacent upper node, it defers the transmission of the received data until the node obtains a sensed data observed by itself. After obtaining the observed data, the node combines the observed data and the received data thus far according to the aggregation factor A_f , and transmits the combined data to the adjacent lower node.

In Fig. 3, at node n2, D41 has to be waited for aggregation until E22 occurs, After E22 occurs, n2 combines D22 and the received data including D41 and transmits the combined data to n1. Note that A_f =1 in this figure.

3. Analysis

3.1 Non-aggregation

We analyze total delay and energy consumption in the data transmission without data aggregation.

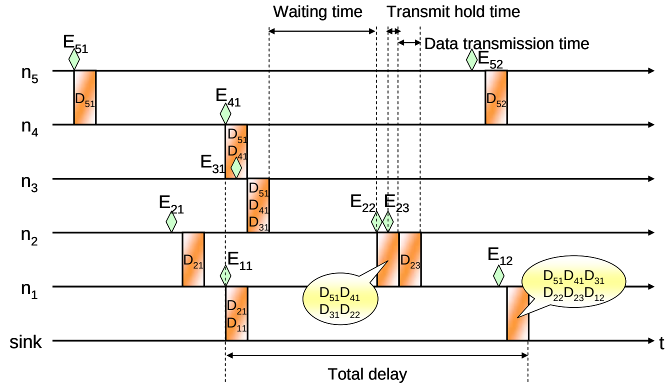

Fig.3 Sequence sample of data aggregation.

3.1.1 Analytic model

Fig. 4 shows the queuing model of non-aggregation data transmission of node ni.

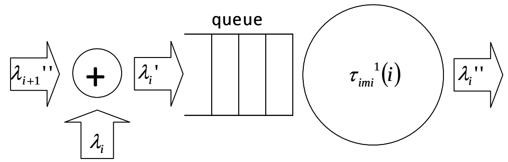

Fig.4 Analytic model of non-data aggregation at ni.

3.1.2 Arrival process to the queue

Data arrives from the upper node n_{i+1} with the rate of λ_{i+1}''. We assume that the original data observed by n_i arrives in Poisson distribution of average λ_i in Fig.4. Therefore, the arrival rate of data to the queue, λ_i' is

$$\lambda_i' = \lambda_{i+1}'' + \lambda_i \quad (1).$$

Since data arrival from the upper node is not according to Poisson, strictly speaking, the process to the queue is not Poisson. However, in this paper for simplicity, we approximate the process to be Poisson. λ_i'' is the data arrival rate to n_{i-1}. This paper also approximates that the arrival process at n_{i-1} follows Poisson distribution with the arrival rate λ_i''.

3.1.3 Service process

The service process becomes data transmission time $\tau^1(i)$. $\tau^1(i)$ is derived from data rate v_c when the data size is Si.

$$\tau^1(i) = \frac{S_i}{v_c} \quad (2).$$

3.1.4 Backoff time

When an event occurred during data transmission, the node waits to transmit data to the lower node. The backoff time $\tau_{imi}{}^c(i)$ is required to avoid collision. This is denoted by the queue and the server in Fig. 4. From the queuing theory, $\tau_{imi}{}^c(i)$ is derived by M/D/1 model. Data comes in Poisson distribution with average λ_i' to the queue. Service time is the constant as shown in (2). As a result of M/D/1[10], we obtain the following equation,

$$L_{imi}(i) = \frac{\alpha_i}{1-\alpha_i} - \frac{\alpha_i{}^2}{2(1-\alpha_i)} \quad (3),$$

where $L_{imi}(i)$ is the number of data waiting to transmit in n_i, and α_i is the utilization of node n_i.

$$\alpha_i = \lambda_i' \tau^1(i)$$

In addition, from the Little's formula, we obtain

$$\tau^c{}_{imi}(i) = \frac{L_{imi}(i)}{\lambda_i'} \quad (4).$$

Backoff time, $\tau^c{}_{imi}(i)$ is calculated by (3) and (4) as follows,

$$\tau^c{}_{imi}(i) = \frac{\tau^1(i)(2-\lambda_i'\tau^1(i))}{2(1-\lambda_i'\tau^1(i))} \quad (5).$$

3.1.5 Total delay

Total delay $T_{imi}(i)$ is derived as follows where the number of the hops from node n_i to the sink is H_i.

$$T_{imi}(i) = \sum_{k=1}^{H_i} \left(\tau^c{}_{imi}(k) + \tau^1(k)\right) \quad (6).$$

3.1.6 Energy consumption

The node n_i transmits observed data and relay received data from the upper nodes. Since the consumed energy of a node H hops far from the sink, $P_{imi}(H)$ is in proportion to the number of times of data transmission, the energy consumption in non-aggregation. $P_{imi}(H)$ is expressed as follows, where P_t and P_r are power required for transmitting and receiving a packet, respectively.

$$P_{imi}(H) = \sum_{k=1}^{H} L(k)(P_t + P_r) \quad (7).$$

3.2 Full data aggregation

We analyze total delay and energy consumption in data aggregation.

3.2.1 Analytic model

Data transmission with full data aggregation is transmitting a data when a sensor node observes an event at itself. Thus, a node keeps data until the node observes any event. When node observes an event, it combines data received previously and observed data and transmit. Fig. 5 shows the model of the data aggregation at node ni. Queue A represents waiting time for an event, whereas Queue B does backoff time for transmission.

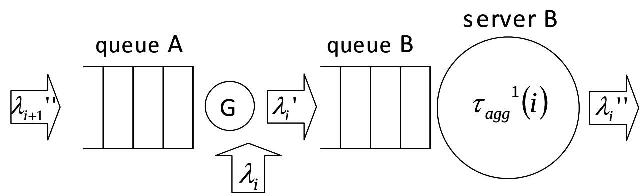

Fig.5 Analytic model of data aggregation at ni.

3.2.2 Arrival process to the queue A

As with the previous section, the arrival process to queue A is assumed Poisson distribution with arrival rate λ_{i+1}''.

3.2.3 Event waiting time

At first, the number of data waiting, $Q_{agg}(i)$ for an event in n_i is derived. To find $Q_{agg}(i)$ in queue A of node n_i, we describe the state transition rate diagram as shown in Fig.6. The basic idea to analysis is that data waits in queue A for the duration according to the exponential distribution of average $1/2\lambda_i$. In the diagram, the state variable is the number of data waiting for an event.

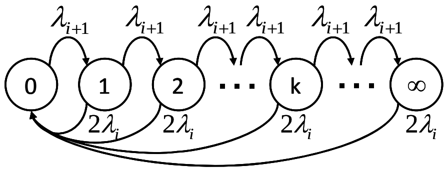

Fig.6 State transition rate diagram.

Let's P_{ik} be the probability when the number of data waiting for an event is k in queue A of n_i. From the diagram, we can derive P_{ik} as follows

$$P_{ik} = \frac{2\lambda_i \lambda_{i+1}{}^k}{(\lambda_{i+1} + 2\lambda_i)^{k+1}} \quad (8).$$

Thus, the number of the data waiting for an event generation in queue A at n_i, $Q_{agg}(i)$ is

$$Q_{agg}(i) = \sum_{k=0}^{\infty} kP_{ik} = \frac{\lambda_{i+1}}{2\lambda_i} \quad (9).$$

Event generation waiting time, $\tau_{agg}{}^e(i)$ is derived by Little's formula.

$$\tau_{agg}{}^e(i) = \frac{\lambda_{i+1}}{2\lambda_i{}^2} \quad (10).$$

3.2.4 Arrival process to the queue B

G in Fig. 5 is the gate which opens when n_i observes an event. The interval of opening the gate G depends on λ_i. The event generation in n_i follows Poisson distribution with average λ_i. Therefore, data arrival to queue B is according to Poisson distribution with average $\lambda_i{}' = \lambda_i$.

3.2.5 Service process in server B

All data received so far in queue A and the observed data are sent to server B. If the aggregation factor $A_f = 1$, these data are compressed into a single data. The service time of the server is directly data transmission time $\tau_{agg}{}^1(i)$,

$$\tau_{agg}{}^1(i) = \frac{1}{(1-\rho)} \frac{S_i}{v_c} \quad (11)$$

Note that hereinafter we assume that $A_f = 1$, but the similar analysis can be done if it does not hold.

3.2.6 Backoff time

Backoff time can be derived from the service time at the server in Fig. 5 as M/D/1. Therefore, we obtain the following equations,

$$L_{agg}(i) = \frac{\beta_i}{1-\beta_i} - \frac{\beta_i{}^2}{2(1-\beta_i)} \quad (12),$$

where β_i is denoted by,

$$\beta_i = \lambda_i{}' \tau^1(i)$$

In addition, from Little's formula, we obtain

$$\tau_{agg}{}^c(i) = \frac{L_{agg}(i)}{\lambda_i{}'} \quad (13).$$

Thus, backoff time $\tau_{agg}{}^c(i)$ is calculated to be,

$$\tau_{agg}{}^c(i) = \frac{\tau^1(i)\left(2 - \lambda_i{}'\tau^1(i)\right)}{2\left(1 - \lambda_i{}'\tau^1(i)\right)} \quad (14).$$

3.2.7 Total delay

The total delay $T_{agg}(H)$ is derived as follows where the number of hops from n_i to sink is H.

$$T_{agg}(H) = \sum_{k=1}^{H} \left(\tau_{agg}{}^e(k) + \tau_{agg}{}^c(k) + \tau^1(k)\right) \quad (15).$$

3.2.8 Energy consumption

The energy consumption is proportional to the number of data transmissions. So,

$$P_{agg}(i) = L_{agg}(i)(P_t + P_r) \quad (16).$$

4. Fundamental Evaluation

Here, analytic results are shown as well as simulated result. The evaluation parameters are shown to table 1.

Table 1 Evaluation parameters

node distance	10[m]
transmit range	11[m]
MAC	CSMA/CA
routing protocol	DSR
datasize	4096[bit]
event generate	100
transmit rate	250[kbps]

In the simulation, each event occurs at each node randomly and independently. Buffer size of each node is infinite. Although analytic model assumes that transmission error is negligible, transmission errors and retransmission may occur in the simulation.

Fig. 7 shows the total delay where $\lambda i=\lambda$. From Fig.7, as the event generation rate increases, delay increases. In data aggregation the total delay is about 3-1,000 times larger than that of non-aggregation when the event generation is rare. Generally, as nodes observe sensing data rarely in wireless sensor networks, the low generation rate has significant. Therefore, as long as total delay is concerned, non-aggregation should be used at a low event generation rate.

Note that the total delay of the data aggregation is concave up. When event generation rate is low, the received data have to wait longer time at queue A, which leads to the large delay. In addition a node is near to the sink, total delay increases because of the large backoff time at queue due to the congestion around the sink.

Comparing the analytic result with simulation, the difference is large at large event generation rate because ignorance of retransmission in analytic model.

Fig. 8 shows energy consumption of both methods. In this figure$\lambda i =\lambda= 5$. The x-axis is total number of nodes in the sensor network. We can see that the larger network size, the more energy is consumed. Especially, non-aggregation consumes much more than aggregation. In non-aggregation, n1, the node nearest to the sink, consumes the largest energy. This is because the nearer a node to the sink, the more data it relays and the more data should be transmitted due to the congestion. Since data aggregation suppresses the traffic, it mitigates the congestion resulting in low energy consumption.

From Fig. 7 and Fig. 8, we found that from a viewpoint of energy consumption data aggregation outperforms, however, from a view point of delay non-aggregation does.

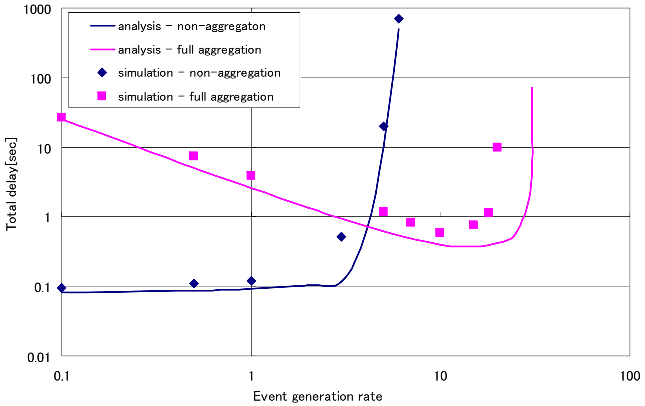

Fig.7 Total delay

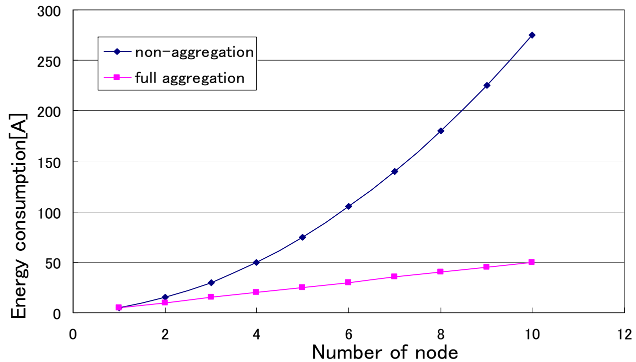

Fig.8 Energy consumption of the whole network

5. Partial data aggregations

In the full aggregation when an event does not occur around ni, data suffers a long delay. To overcome this problem, we propose two partial aggregation methods, random partial aggregation (RP) and waterfalls random partial aggregation (WRP).

5.1 Random partial aggregation (RP)

In RP, some data are aggregated but others are not. As shown in Fig. 9, RP simply opens the gate G randomly according to exponential distribution. The rate of pseudo arrival of the data is denoted by λ_i^D, which is called random pushing rate. In RP, all random pushing rates are identical to nodes, i.e., $\lambda_i^D = \lambda^D$.

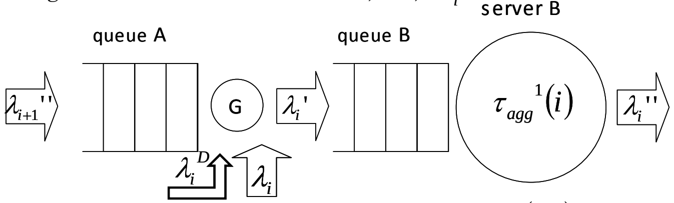

Fig. 9 Random partial aggregation (RP)

The analysis can be done straightforwardly by replacing λ_i in aggregation with $\lambda_i + \lambda^D$. Fig. 10 shows an analysis result of RP. RP performance is between those of non-aggregation and aggregation. If λ^D is zero, it means fully aggregation and if λ^D is infinite, it means fully non-aggregation. We can see in the figure that λ^D can control the total delay and energy consumption by the partial aggregation. According to the requirements of the application, the partial aggregation can build the network which is most preferable.

5.2 Waterfalls RP aggregation (WRP)

WRP is based on RP. The difference is setting λ_i^D. From the Fig. 7, non-aggregation is preferable at low data generate rate. Nodes nearer the sink transmit larger traffic, which is equivalent to posing the lower nodes large data generate rate. Thus, in WRP λ_i^D is set to a smaller value of pushing rate if n_i is near the sink as in Fig.11. In other words, data are rarely aggregated at nodes far from the sink to suppress delay. Fig. 12 and Fig. 13 show simulated results of WRP as well as non-aggregation, full aggregation and RP.

As for WRP, the total control of delay and energy consumption is more flexible than RP. Compared with RP when λ_i^D is big, the total delay of WRP is small, because backoff time of lower node is small. And when λ_i^D is small, the total delay of WRP is small, because event waiting time of upper node is small. Therefore, we can build low delay network to set λ_i^D for each node by WRP.

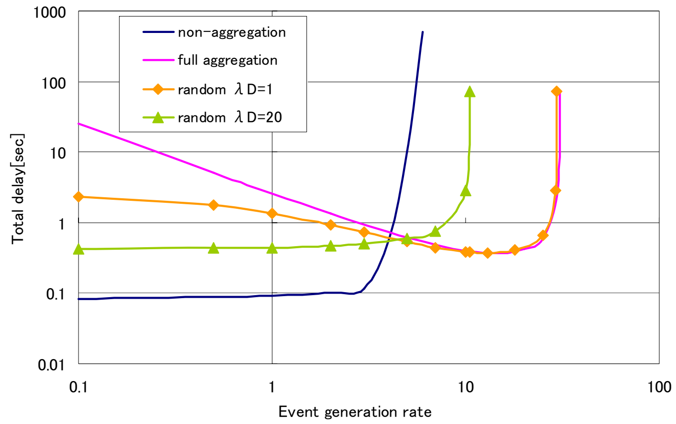

Fig. 10 Total delay of RP

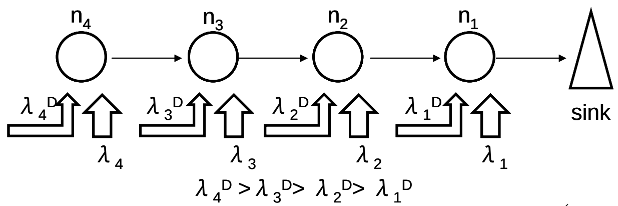

Fig. 11 Waterfalls random partial aggregation (WRP)

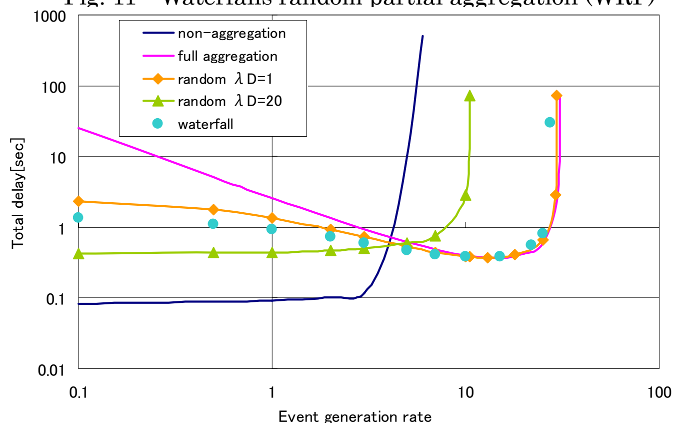

Fig. 12 Total delay of RP and WRP

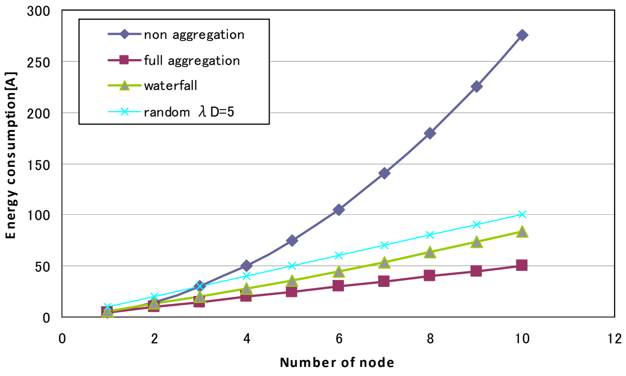

Fig. 13 Energy consumption of RP and WRP

6. Conclusions

This paper discussed the data aggregation from view point of trade off between communication delay and energy consumption. For the tandem sensor networks the Markovian model as well as simulation results shows that although from a viewpoint of power consumption full aggregation is preferred, the delay is very large compared with non-aggregation method when a sensing event occurs sparsely in time. Based on the results, to suppress the delay, this paper proposes two partial aggregation techniques. In RP, the waiting data can be transmitted to the lower node even without the sensing data arrival. RP can control the delay by a single parameter, random pushing rate. In WRP, each node has independent random pushing rate according to the distance from the sink. Farther nodes from the sink have larger random pushing rate. The simulation results show the controllability of RP and the efficiency of WRP.

Although the network model is simple, the analytic result can be applicable to more complex structure. As shown in Appendix, for a tree topology data aggregation is effective for higher tree. So, we are engaging in applying RP and WRP to more complex networks including cross and tree topologies. Finding an optimal random pushing rate vector for each node in WRP and developing more sophisticated WRP with adaptively assignment of random pushing rates according to the sensing data generation and the network traffic are also the future works.

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APPENDIX

A) Discussion on the efficiency in tree topology network

Now we consider a simple tree network whose height is m. Each node has k branches. Fig. A1 shows a sample with m=3 and k=3. Let's assume that each node sends one data packet. Then, the efficiency defined by the rate of total number of sending packets of non aggregation and full aggregation is derived as,

$$\frac{mk^{m+1} - (1+m)k^{m} + 1}{(k-1)(k^{m}-1)} \cong m \qquad \text{(A.1)}$$

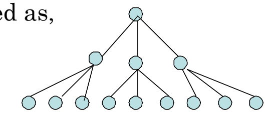

Fig. A1 A tree topology.

(A.1) means that the data aggregation has approximately linear efficiency to the tree height.