

# Information-Aware Traffic Reduction for Wireless Sensor Networks

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**Abstract**—Environmental monitoring is one of the most popular applications in wireless sensor networks. Although it is important to obtain a continuous record of the environment, users may gain enough information without receiving every routine sensor measurement. Reducing unnecessary traffic allows better utilization of the network resources. However, it is uneasy to decide on when and what kind of traffic to reduce in a dynamically changing environment. In this paper, we study the problem of information-aware traffic reduction for wireless sensor networks. We propose a two-step information-aware traffic reduction algorithm to address this problem. First, we provide a distributed and real-time algorithm for sensors to classify their measurements and report them selectively based on the importance of information. Then, we propose a bandwidth allocation algorithm to assign different forwarding probabilities to packets considering both the information quality and the network load. Our algorithm can be implemented and integrated easily with existing routing protocols to maximize the quality of information to the users, while reducing the amount of network traffic. We evaluate our approach based on the real sensing measurements to demonstrate the quality of information achieved. Simulations are also conducted to evaluate the performance of our proposed scheme in a larger network.

## I. INTRODUCTION

Wireless sensor network (WSN) is usually a set of small sensing devices with limited communication range. They monitor the environment by reporting sensing measurements to the sink(s) with multihop wireless communications. Sensors may perform sensing continuously which result in a steady volume of data towards the sinks. While routine data are essential for reporting the normal measurements on the environment, not all measurements are necessary to provide enough information to the users. Some measurements may be redundant if there is only a steady change of temperature in the environment. The network bandwidth can be reserved to report more critical unusual events which require faster delivery or “better QoS”. For example, a sudden increase of temperature detected by the sensors in a forest may need a fast delivery for high priority packets with better quality of service in terms of shorter delay, higher bandwidth, etc.

A number of approaches have been proposed to provide QoS for sensor networks which reduce network congestion by checking the traffic level of neighboring nodes and controlling the transmission rate [1], [2], [3]. The above mechanisms inform the source nodes with feedback messages to reduce the data rate. However, The feedback messages may increase the network overhead. Also, they seldom consider the quality

of information eventually obtained by the users after reducing the network traffic.

We study information-aware traffic reduction for wireless sensor networks in this work. Our major goal is to reduce the routine data traffic in the network, while providing satisfactory quality of information to the users. We focus on general environmental monitoring applications which collect sensing data continuously over a long period of time and aim at providing better quality of information and shorter packet delay. The major challenges include extracting important data from a series of measurements in real time and maximizing the information obtained by the end users given the limited network capacity. In addition, the algorithm should be distributed, lightweight and suitable for the fast-changing sensing environment as well as the dynamic network load.

Our approach wisely selects important data to report to the sink. Sensors control the packet rates according to the information that the packets carry and the current network traffic level in order to provide both high quality of information and good quality of service. Information-aware traffic reduction allows better utilization of the network capacity by reducing the relatively less important traffic and reserving better resources for the high priority data. Our algorithm can be integrated easily with existing QoS routing algorithms to provide better QoS and more valuable information to the end users.

The remainder of the paper is organized as follows. In Section II, we describe some related work in the area. In Section III, we give the network model and formulation of the information-aware traffic reduction problem. We present our information-aware data selection and reconstruction algorithms in Section IV. We then present our adaptive traffic reduction algorithm and its integration with the QoS-aware routing algorithm in Section V. Section VI summarizes the simulation results that we have obtained, and we conclude the paper in Section VII.

## II. RELATED WORK

A number of congestion control algorithms have been proposed for wireless sensor networks [2], [4], [5]. Wan et al. [1] propose an energy efficient congestion control scheme for sensor networks called CODA (COngestion Detection and Avoidance), which includes receiver-based congestion detection, open-loop hop-by-hop backpressure, and closed-loop multi-source regulation. Hull et al. [3] examine three techniques to mitigate congestion in WSN, which includes hop-by-hop flow

control, rate limiting source traffic, and prioritized medium access control (MAC). Ee et al. [2] propose a distributed algorithm for congestion control and fairness in many-to-one routing, which measures the average transmission rate, then divides and assigns the average to downstream nodes equally. Although the above work can mitigate network congestion, they do not consider the quality of information achieved by the end users when suppressing the traffic. Moreover, most of the existing work require feedback from sensor nodes which result in extra overhead in the network. Our information-aware traffic reduction approach focuses on the quality of information achieved by the users. It is distributed and lightweight since all decisions are taken locally by the nodes, and it requires no feedback messages from the congested nodes.

Some related work on adaptive samplings have also been proposed to decrease the energy consumption of sensors and prolong the network lifetime. Gedik et al. [6] suggest to collect data using a dynamically changing subset of nodes as samplers, whereas the values of the nonsampler nodes are predicted through a probabilistic model. Similarly, Willett et al. [7] achieve adaptive sampling by selecting activating sensors with the backcasted information from the fusion center. Apart from the spatial approaches, some adaptive sampling approaches on the temporal domain have been considered. Kho et al. [8] propose a decentralized algorithm to minimize the uncertainty of sensing data, subject to the constraint of a limited number of samples taken per node. Different from adaptive sampling, our approach focuses on data delivery from the sources to the sink. Our information-aware traffic reduction algorithm can be applied after various sampling schemes to adapt to the network traffic without the risks of missing any unusual events.

Apart from the above, Bisdikian [9] introduces the general term “Quality of Information (QoI)” which measures attributes like timeliness, accuracy, reliability, completeness, relevance when detecting events and making decision in WSN. We are inspired by this concept and we consider QoI as the accuracy and relevance of data to the users in this work. Accuracy accounts for whether the data received by the users can describe the environment correctly. Relevance concerns about whether valuable information of high interest are delivered to the users. Zaheki et al. [10] also propose an quality of information aware framework for fault detection and event detection which suggests to use QoI as a performance metric associated with the end result produced by a sensor network. We share a similar idea of combining network quality of service with the quality and integrity of sensor data sources here, but we focus on data delivery and traffic reduction in this paper.

### III. INFORMATION-AWARE TRAFFIC REDUCTION

#### A. Network Model

In many applications, sensors take readings from the environment regularly and then forward the data to the sinks. It is common in many environmental monitoring applications to have two kinds of data, namely (1) routine data, which reports

the steadily change of the environment throughout long period of time, and (2) unusual events of particular interest will occur unexpectedly, and the information related to such events will require fast transmission to the sink(s) [11], [12].

We consider a network with sensors distributed over some open or built areas. The sensor nodes take measurements and forward packets containing their measurements toward one or more sink nodes. We define  $\Delta t$  as the time interval that sensors take measurements from the environment. The value may depend on the capability of the sensor and the frequency required to capture the unusual events in a specific application. Let  $x_0, x_1, x_2, \dots, x_N$  be the sensor readings at time  $t_0, t_1, t_2, \dots, t_N$ , where  $t_k = k\Delta t$ . The sensor measurement  $x_k$  may fall in a range  $[a, b]$ . To distinguish the routine data and significant events, each sensor keeps an expected weighted moving average  $S_t$  on the measurement as:

$$S_t = (1 - \alpha)S_{t-1} + \alpha x_{t-1}. \quad (1)$$

It then calculates the sensor measurement deviation,  $Dev_t$ , as an estimation of how much  $x_t$  typically deviates from  $S_t$ .

$$Dev_t = (1 - \beta)Dev_{t-1} + \beta \|x_t - S_t\|; \quad (2)$$

Since sensor nodes have limited wireless communication range, multi-hop routing is generally required to forward the data to the sinks. Network congestion may occur if the traffic load is too heavy in the network which may delay the delivery of the sensing data. This can be avoided by controlling the traffic rate in the network. The nodes may drop some of the packets selectively based on the importance of information  $w$  in the packets. Intuitively, the information is more important and valuable if the reported data deviates more from the predicted value  $S_t$ , hence, we select  $w = \|x_t - S_t\|$ . The importance of information can be further divided into multiple levels,  $w_i$ , where  $i = 1, 2, \dots, m$ .

#### B. Problem Formulation

Each sensor monitors the incoming data rate  $\lambda_{in} = \sum_{i=1}^m \lambda_i$ , where  $m$  is the maximum level of importance among the data and  $\lambda_i$  is incoming rate of data with importance level  $i$  at a node. Then, the sensor forwards the packets selectively according to  $w_i$ , while maximizing the information delivered. There is a maximum affordable traffic rate  $\mu$  in a node, such that  $\lambda_{in} \leq \mu$ . Information-aware traffic reduction can be formulated as a fractional knapsack problem [13] as follows.

#### Objective

Maximize

$$\sum_{\forall i} w_i \mu_i \quad (3)$$

#### Subject to

$$\sum_{\forall i} \mu_i \leq \mu, \quad (4)$$

$$0 \leq \mu_i \leq \lambda_i, \quad (5)$$

where  $w_i$ ,  $\lambda_i$ ,  $\mu_i$  and  $\mu$  are positive scalars. Assume without loss of generality that

$$w_1 \geq w_2 \geq \dots \geq w_m, \quad (6)$$

which represent the importance of information at different levels.

The data rate allocated by the sensor to the data with importance level  $w_i$  is denoted by  $\mu_i$ , where  $\mu_i = \lambda_i p_i$  and  $p_i$  is the transmission probability of the corresponding packets. The objective is to maximize the information gain while keeping the data rate in a node smaller than the maximum affordable level. The fractional knapsack problem is solvable by a greedy algorithm, provided that the value per weight of each items can be achieved and sorted [13]. The packets in the network can be modelled as the items with equal weight which have different values. The weight in our problem can be considered as the network load for carrying the packet. The value is measured as the importance of data contained in the packet. Unlike the traditional fractional knapsack problem in which the items are fixed, the incoming packet rates and the value of packets are dynamically changing in sensor networks. We hence require a real-time and distributed algorithm for sensors to judge the importance of the measurements and select the important data to report. We also provide a bandwidth allocation algorithm for sensors to calculate the probability to forward the packets based on the quality of information and the network load.

#### IV. TRAFFIC REDUCTION AT SOURCE NODES

##### A. Selective Transmission at Sources

In many environmental monitoring applications, the sampling rate of sensors is set to the minimum value that allows users to detect the unusual events or observe the change of the environment. Consider a temperature monitoring application in a glacier, the scientists may want to keep a record of temperature with every change less than  $0.5^\circ\text{C}$ , but they do not need a record of small changes as precise as  $0.2^\circ\text{C}$ . They can then set the expected change on the data values between 0.2 and 0.5 in their application. Under this requirement, the data reporting rate can be greatly reduced if the temperature changes only steadily. For example, some data with changes smaller than 0.2 may not be reported.

We then propose a real-time algorithm for selective transmission at the source nodes as shown in Algorithm 1. Each sensor takes measurements and calculates  $S_t$  and  $Dev_t$  every time interval  $\Delta t$ . It then classifies the data as high priority data  $H$  if the difference between the current measurement and the estimated measurement is greater than a threshold, i.e.  $\|x_t - S_t\| \geq \varepsilon$ . This indicates that there is an unusual event occurred. For all the remaining routine data, they are marked as low priority  $L$ . Each sensor also keeps track of the sensor measurement deviation  $Dev_t$ . If  $Dev_t$  is greater than the concerned threshold  $\delta$ , then the data will be reported. Otherwise, these routine data will be reported only every  $R_t$  time intervals, which is measured by a counter  $C_t$ . Note that the value  $R_t$  is initialized as 1 at the beginning, then it will

increase gradually if  $Dev_t$  is constantly small. However, it will be set to 1 again if  $Dev_t > \delta$ .

Reducing the retransmission rate at sources can reserve more network resources to provide better quality of service for more important data. The missing routine data between two reported measurements can be reconstructed by interpolation, e.g. linear interpolation, at the sink.

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#### Algorithm 1 Adaptive data transmission at sources

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for each time unit  $\Delta t$  do
  Take measurement  $x_t$ ;
   $S_t = (1 - \alpha)S_{t-1} + \alpha x_{t-1}$ ;
   $Dev_t = (1 - \beta)Dev_{t-1} + \beta \|x_t - S_t\|$ ;
  if  $\|x_t - S_t\| \geq \varepsilon$  then
    Mark data as  $H$ ;
    Report the data;
     $R_t = 1$ ;
     $C_t = 0$ ;
  else
    Mark data as  $L$ ;
    if  $Dev_t > \delta$  then
      Report the data;
       $R_t = 1$ ;
       $C_t = 0$ ;
    else
      if  $C_t == R_t$  then
        Report the data;
         $C_t = 0$ ;
        if  $Dev_t < \delta/2$  then
           $R_t++$ ;
        end if
      else
         $C_t++$ ;
      end if
    end if
  end if
end for

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##### B. Reconstructing Missing Routine Data

The skipped routine data can be reconstructed at the sink by linear interpolation for its effectiveness and efficiency, though other interpolation mechanisms can also be applied. Given a set of  $k$  data points, i.e.  $(x_0, t_0)$ ,  $(x_1, t_1)$ ,  $(x_2, t_2)$ , ...,  $(x_{k-1}, t_{k-1})$ ,  $(x_{k+1}, t_{k+1})$ , where the data at  $t_k$  is missing. The missing data  $x_k$ , where  $t_{k-1} < t_k < t_{k+1}$ , can be obtained by the reported data  $x_{k-1}$  and  $x_{k+1}$  as

$$x_k = x_{k-1} + \frac{t_k - t_{k-1}}{t_{k+1} - t_{k-1}}(x_{k+1} - x_{k-1}), \quad (7)$$

The absolute error  $\xi_k$  of the reconstructed data at time  $t_k$  can be measured as

$$\xi_k = \|r_k - x_k\|, \quad (8)$$

where  $r_k$  is the real sensing measurement from the environment at time  $t_k$ .

The accuracy of the reconstructed data from a sensor over time  $t$  can be measured by the mean absolute error (MAE) and the root mean square error (RMSE) as

$$MAE = \frac{\sum_{t=1}^N \|r_t - x_t\|}{N} \quad (9)$$

and

$$RMSE = \sqrt{\frac{\sum_{t=1}^N \|r_t - x_t\|^2}{N}}. \quad (10)$$

MAE and RMSE can be used together to diagnose the variation in the errors of a set of reconstructed data. The MAE is a linear score which means that all the individual differences are weighted equally on average. On the other hand, RMSE is a quadratic scoring rule which measures the average magnitude of the error.

## V. TRAFFIC REDUCTION ALONG INTERMEDIATE NODES

We propose an information-aware traffic reduction algorithm to reduce the routing data traffic along the intermediate nodes, while providing satisfactory quality of information to the users. We integrate the algorithm with an existing QoS-aware Random Re-Routing (RRR) algorithm [11], [12] to provide quality of service in the delivery of unusual events and routine data.

### A. QoS-Aware Random Re-Routing for Routine Data

RRR is designed to provide differentiated QoS for an environment with unusual event data and routine data in sensor networks which shares the same settings as the environmental monitoring applications in our work. Although RRR is selected here, our traffic reduction algorithm can actually integrate with other existing routing algorithms easily.

In RRR, each node  $j$  observes the level of arriving traffic of unusual events  $\lambda_H$ . If this rate  $\lambda_H$  does not exceed a threshold  $\theta_H$ , then the node forwards all packets it receives along their preferred (e.g. shortest or best QoS) path towards their destinations. Obviously the preferred path may be determined by criteria such as the minimum delay, greatest security, lowest power consumption, smallest loss, etc. However, if  $\lambda_H \geq \theta_H$ , then the preferred path will be reserved for forwarding the unusual event packets and only the secondary paths will be used for the routine data packets.

More specifically, each node  $j$  ranks its neighboring nodes  $j_1, \dots, j_n$  so that  $j_1$  is located closest to the sink in number of hops, and  $j_n$  is the one which is the farthest away. Then, node  $j$  forwards unusual event packets to neighbors  $j_1, \dots, j_q$ , and forwards all routine data packets to the remaining neighbors  $j_{q+1}, \dots, j_n$ . This algorithm allocates the best route for transmitting important event data, while routine data are pushed aside to the remaining routes to achieve quality of service [11], [12].

### B. Traffic Reduction on Routine Data

Our information-aware traffic reduction algorithm works closely with the routing scheme. Similar to RRR, traffic reduction at intermediate nodes applies only when the network traffic level is heavy. The mechanism can relieve network congestion by reducing less important routine data, while preserving high quality of information to users.

Moreover, routine data packets travel through longer secondary paths in RRR to reserve better QoS paths for unusual

events. The prolonged paths may increase the packet travel delay of the routine data which can be reduced by controlling the traffic rate of the packets. Dropping some routine data packets can keep the average network traffic level nearly the same in randomized routing.

When an unusual event packet arrives, a node always forwards the packet to the next hop. On the contrary, a node forwards a routine data packet with only a probability  $p_i$ .  $p_i$  can be obtained by our bandwidth allocation algorithm (see Algorithm 2). Each node monitors the incoming data rates and runs this algorithm periodically or when there is a significant change in the incoming data rates. A node will forward as much as possible of the packets contain the most important information. If there is still enough network capacity, it takes as much as possible of the next most important packets. The process continues until the network capacity is fully utilized.

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### Algorithm 2 Bandwidth allocation algorithm

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for all  $i$  do
   $p_i = 0$ ;
end for
 $\mu' = \mu$ ;
 $i = 1$ ;
while  $\mu' > 0$  do
  if  $\mu' \geq \lambda_i$  then
     $p_i = 1$ ;
     $\mu' = \mu' - \lambda_i$ 
  else
     $p_i = \mu' / \lambda_i$ ;
     $\mu' = 0$ ;
  end if
   $i++$ ;
end while

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This mechanism reduces the traffic of the less important routine data and shortens the average packet travel delay, but it still preserves a high quality of information to the users. Note that  $p_i$  represents the probability that a packet is forwarded to the next hop. This value is affected by both the importance of the packet and the network traffic level of the node. It may be different from node to node and changing dynamically.

## VI. PERFORMANCE EVALUATION

### A. Quality of Information

We evaluate the quality of information achieved with the real sensing data collected from the SensorScope network [14], which is deployed on the Plaine Morte glacier for monitoring the temperature, humidity, wind speed and direction. There are 13 sensors in the network and a sink located at the center. We simulate our information-aware traffic reduction algorithm based on the sensor measurements of the surface temperature. The absolute errors between the real sensing data and the reconstructed sensing data from our algorithm are evaluated.

Figure 1 shows the data collected by a sensor, together with the data points reported by our adaptive transmission algorithm at  $\varepsilon = 1.0$  and  $\delta = 0.5$ . Some data points are skipped in our algorithm to reduce the traffic. From the figure, the surface temperature is changing quite steadily, except there

is an unusual event occurred at 1870s. The missing data points will be reconstructed when they are received at the sink. The resulting data are shown in Figures 2 and 3. Due to the limited space, only the results in  $t = 1000 - 1300s$  and  $t = 1800 - 1950s$  are shown. We compare our adaptive transmission algorithm with the static transmission algorithm which reports one out of every three data at regular time interval. The two algorithms report almost the same number of data to the sink for fair comparison. The absolute error of the reconstructed data are presented in Figures 4 and 5. Figure 4 shows that the absolute error in adaptive transmission is smaller than  $0.7^\circ C$  constantly, while the absolute error in static transmission may go up to  $1.4^\circ C$ . It indicates that adaptive transmission can provide better quality of information and less error than static transmission, though the two algorithms are reporting at the same data rate on average. The reason is that the regular dropping of data samples in static transmission may miss some important information, while adaptive transmission only skip the relatively less important data. This is even more obvious at  $t = 1870s$  in Figure 5 when an unusual event occurs with a sudden increase of the temperature. Static transmission misses several data points of the unusual event which leads to great absolute errors. The mean absolute error of adaptive transmission and static transmission are  $0.136^\circ C$  and  $0.152^\circ C$  respectively. Their corresponding root mean square error are  $0.065^\circ C$  and  $0.171^\circ C$ . The results demonstrate that adaptive transmission can achieve lower mean absolute error than static transmission and avoid errors with large magnitude.

We further evaluate the quality of information with selective forwarding. We consider a sensor which requires two-hop communication to the sink. Some packets are dropped by the intermediate nodes in routing due to network congestion. Again, we calculate the absolute error and root mean square error in both adaptive transmission and static transmission. The average absolute error of adaptive transmission and static transmission which are  $0.202^\circ C$  and  $0.377^\circ C$ . Their corresponding root mean square error are  $0.335^\circ C$  and  $0.535^\circ C$ . The results indicate that adaptive transmission can achieve more accurate data, and hence better quality of information, than static transmission. It is because the packets are classified and marked according to their information value in adaptive transmission and only less important data are dropped by the intermediate nodes. On the contrary, some important data may be dropped in static transmission to relieve network congestion, so some valuable information may be lost and the reconstructed data may not be so accurate. Hence, the absolute errors in static transmission are not as low as those in adaptive transmission.

### B. Packet Travel Delay

Next, we conduct simulations using the *ns-2* tool [15] to evaluate our traffic reduction algorithm in a larger network. The simulation parameters are summarized in Table I. They are selected so as to be compatible with other studies of WSNs [16], [17], [18].

The simulations we have conducted focus on a WSN which

TABLE I  
SIMULATION PARAMETERS

Network area	400m*400m
Number of sensor	400
Sensor distribution	Uniform random
Location of Sink	Center of area
Radio range	40m
MAC layer	IEEE 802.11
Unusual event sources	4
Routine data sources probability $p_L$	0.1
Routine data dropping probability	$p_d$
Data rate of unusual events $\lambda_H$	5pkt/s
Data rate of routine data $\lambda_L$	1pkt/s

collects and reports significant events and routine data to the sink. Any of the sensors has a probability  $p_L$  to be the source of routine data and generates data independently of the other nodes. Under normal conditions the sensors report routine data to the sink at a low data rate. Unusual events are assumed to occur infrequently, and in the simulations we have included four nodes which simulate the sources of such events and generate a high traffic rate.

The network considered has a total of 400 nodes and a sink. The node positions are all randomly distributed within a 400m x 400m square (m=metres). The communication range of a node is 40 meters, and the sink is located at the center of the square with coordinate (200, 200). The routine data packet rate is 1 pkt/s with  $p_L = 0.1$ , while the unusual event traffic rate is 5 pkt/s at 4 nodes in the network.

We evaluate the packet travel delay in RRR with traffic reduction on routine data. Traffic starts at 0s with no unusual events, followed by four unusual events to occur at 40s. The sources of unusual events are located at (100, 100), (100, 300), (300, 100), (300, 300), while the reference sources of routine data are located at (60, 200), (200, 60), (200, 340), (340, 200) with equal distance to the sink for comparison.

Figure 6 shows the travel delay of packets with dropping probability  $p_d = 0.1$ . In the beginning of the simulation, sensors forward the packets with RRR as they are not sure whether there is unusual event in the network. After exploration in the first 20s, they switch to traditional shortest path geographic routing as there is no unusual event. At 40s, four unusual events occur. Each sensor keeps tracking the incoming packet rate  $\lambda_H$ . Since  $\lambda_H > \theta_H$ , sensors change to RRR again, such that unusual event packets achieve much lower travel delay than the routine data packets. To reduce the amount of routine data, traffic reduction is applied at 80s. The routine data packets are dropped with a probability  $p_d = 0.1$ . The figure shows that the packet delay of routine data drops to a level that is comparable with that in shortest path geographic routing. It indicates that dropping a small amount (10%) of routine data packets in intermediate nodes persistently can reduce the traffic load and the packet delay effectively. Note that there are more fluctuations on the line of Routine Data

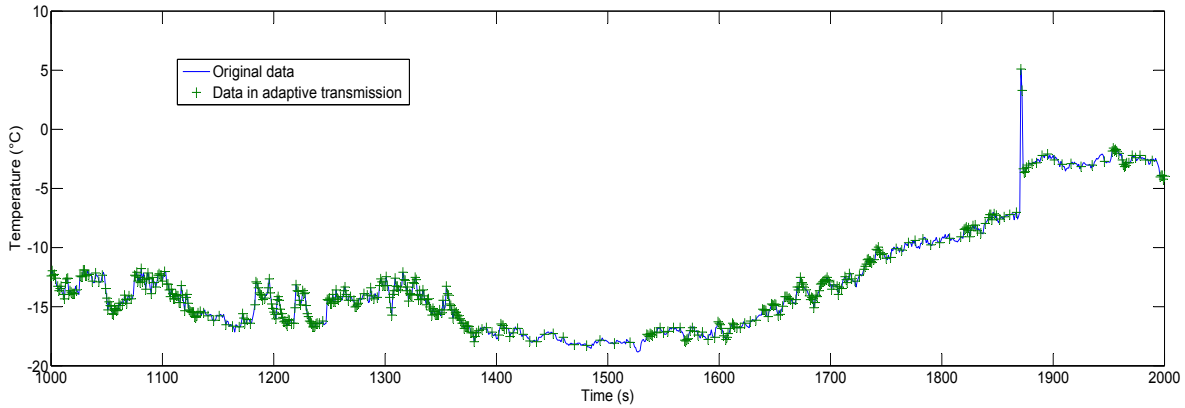


Fig. 1. Data reported by sensor in adaptive transmission.

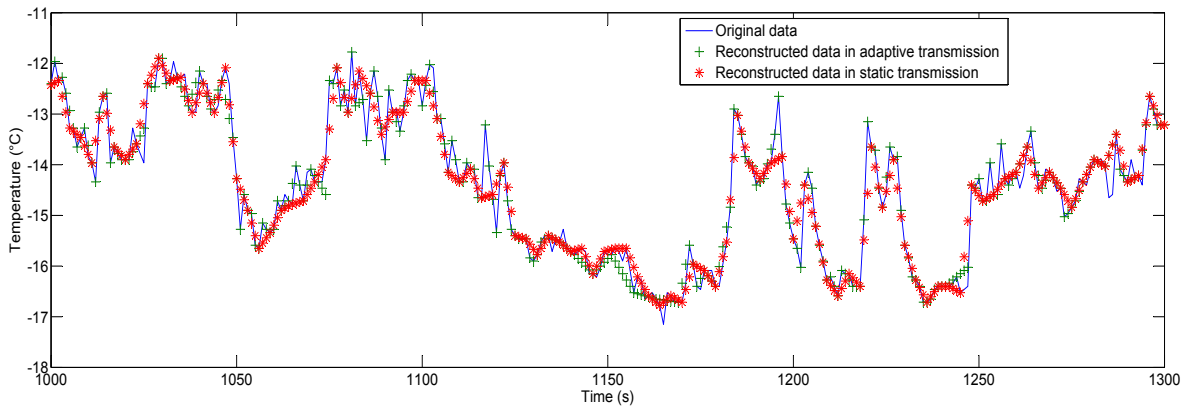


Fig. 2. Reconstructed data in adaptive transmission and static transmission with only routine data.

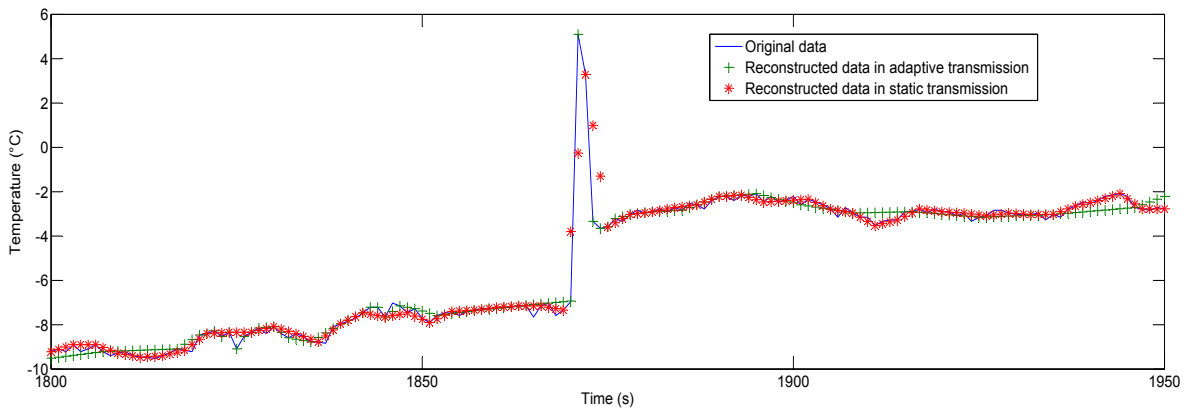


Fig. 3. Reconstructed data in adaptive transmission and static transmission with both routine data and unusual event.

(Reference Sources) than Unusual Events as the paths are selected with more randomness for the Routine Data.

Figure 7 again shows the differentiated QoS achieved be-

tween unusual events and routine data with  $p_d = 0.2$ . The results also demonstrate that the packet travel delay of routine data and event data are further reduced when  $p_d$  increases.

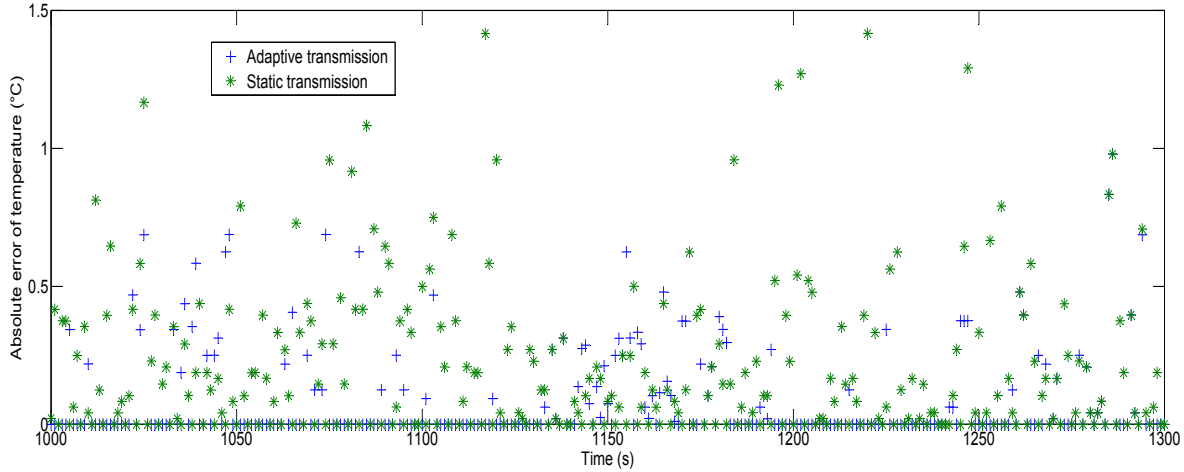


Fig. 4. Absolute error of temperature in adaptive transmission and static transmission with only routine data.

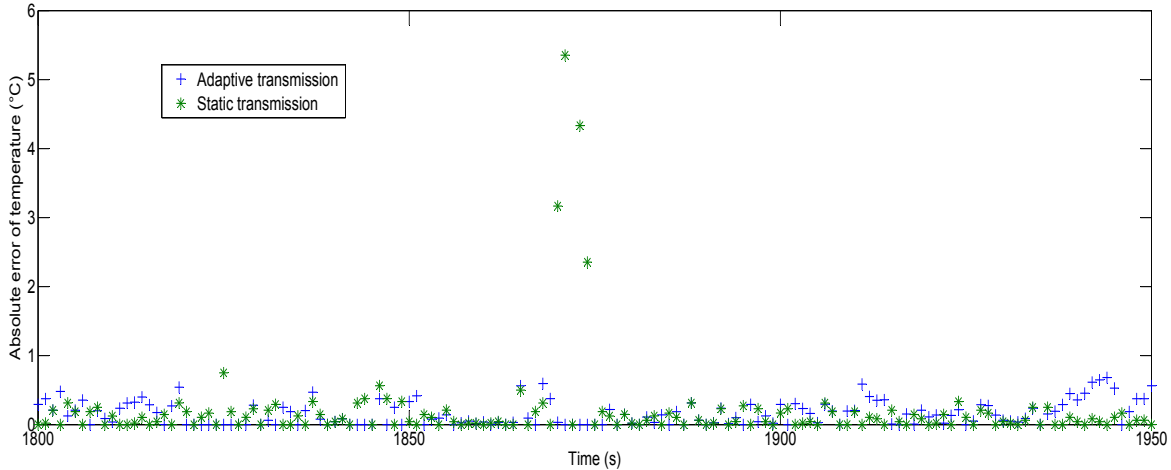


Fig. 5. Absolute error of temperature in adaptive transmission and static transmission with both routine data and unusual events.

### C. Packet Rate

We study the packet rates of unusual events and routine data in presence of RRR and traffic reduction in the same experiment. Figure 8 shows that the packet rate of unusual events keeps steadily at 5pkt/s after the events occur at 40s. At 80s, reduction of routine traffic is applied by dropping routine packets with probability  $p_d = 0.1$ . As a result, the packet rate of routine data drops from 1pkt/s to 0.5pkt/s on average. The packet rate drops further to 0.3pkt/s on average when we set  $p_d = 0.2$ .

## VII. CONCLUSIONS

In this paper, we proposed an information-aware traffic reduction algorithm for sensors to provide satisfactory quality of information, while reducing unnecessary routine data traffic. Our algorithm allows sensors to classify the sensing data in

real-time and report them to the sink adaptively according to their importance levels and the network load. Our bandwidth allocation algorithm decides the forwarding probability of the packets at the intermediate nodes which can adapt to the dynamic change of the network traffic. This approach provides not only high quality of information to the users, but also reserves more network capacity to achieve high quality of service in data transmission. We evaluated our algorithm by simulations based on real sensor measurements. The results showed that our algorithm can effectively reduce network traffic and achieve both high quality of information and low packet delay.

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Fig. 6. Unusual events achieves lower packet travel delay after RRR is applied at 40s, while the delay of routine data increases as they are spread aside to some secondary paths. At 80s, traffic reduction is adopted by dropping the routine data packets with probability  $p_d = 0.1$  to reduce the network traffic and the packet delay.



Fig. 7. The packet travel delay is further reduced when the dropping probability increases to  $p_d = 0.2$ .

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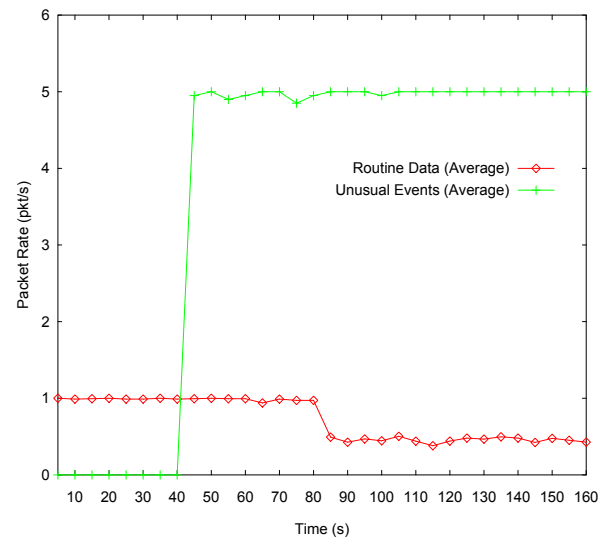


Fig. 8. The packet rate of routine data is reduced when the routine data packets are dropped with a probability  $p_d = 0.1$ .

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