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Quality-of-Information Aware Data Delivery for Wireless Sensor Networks: Description and Experiments

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***Abstract*— Sensor networks have become increasingly popular for a wide range of environmental monitoring and event detection applications. Sensors need to report data to the sinks without missing any important information or unusual events, though reporting large amount of data is infeasible for wireless sensor networks as they usually have limited network capability and energy. In this paper, we propose a quality-of-information aware and energy-efficient data delivery service to report data from sensors to the sinks. Our framework provides high quality-of-information to the users with high data accuracy, short packet delay and low message overhead. Data packets are delivered selectively via different paths based on the information that they are carrying. Packets carrying significant information will be routed with higher priority, while packets with less importance might be dropped or delivered along some slower paths. We propose and implement a routing algorithm based on the SPEED protocol to reduce the number of messages without degrading the quality-of-information. Our work is evaluated by both simulations with real data and real experiments. The experimental results show that our approach can provide high data accuracy and low packet delay with the number of packets significantly reduced.**

Keywords- Quality-of-information, data delivery, wireless sensor networks, experiments

I. INTRODUCTION

Advances in computing and communication technologies have ushered in a class of intelligent wirelessly networked sensor systems that typically have hundreds, even thousands of tiny interconnected sensing devices. These devices collaborate to form a coherent interconnected network called a Wireless Sensor Network (WSN). A typical WSN deployment is tasked with monitoring the environment or detecting an event of interest. Potential applications include habitat monitoring, forest monitoring, military intelligence gathering and utility grid monitoring, etc [1, 12].

The small physical nature of sensors and the need for low production cost limit their capabilities. Sensors usually have limited transmission ranges, limited computation power and energy. Energy-efficiency is very important in WSN because it determines how long the network can operate. Feaney and Nilsson have shown by empirical studies that the fixed overhead cost for sending and receiving data is very high [6]. Dunkels et al. further solidify this point by measuring the energy consumption of the main components in the sensors [5]. Intuitively, reducing the number of messages sent or received could reduce the energy consumption of sensors. This paper investigates efficient data delivery with reduction of messages for saving energy and prolonging network lifetime, while achieving good quality-of-information.

Quality-of-information (QoI) captures a collection of attributes, such as timeliness, accuracy, reliability, throughput, etc. [3]. Single or multiple attributes could be considered based on different requirements of applications. Data delivery within WSN is carried out by multi-hop routing. It is possible to have some preprocessing on raw data before delivery. We believe that data delivery should consider quality-of-information to the users as well as integrate data selection and routing coherently for better performance. In this work, we will propose and implement a three-step solution to achieve this goal. The first step in our framework is adaptive data selection, followed by QoI-aware routing and data reconstruction at the sinks.

The remaining of the paper is organized as follows. Section II presents the related work in the area. Section III describes our proposed QoI-aware data delivery framework. We present our experimental results in Section IV and conclude the paper in Section V.

II. RELATED WORK

Quality-of-information in sensor networks was first proposed by Bisdikian et al. [3, 15] to indicate the effectiveness of the data provided to the applications. A related topic is quality-of-service (QoS) which focuses more on the network layer protocols, rather than the application layer services. QoI also considers data in the broader context and it is concerned more about how useful the data are to the application. It could be considered by multiple layers in the protocol stack to optimize the network performance.

There is a close relationship between sensor readings in the temporal and spatial domains. Sampling techniques have been proposed to take advantage of this relationship. In ASAP [7], data are spatially sampled by a dynamically changing subset of nodes as samplers. The sensor readings at the non-sampled nodes are then predicted by a probabilistic model. Kho et al. focused on adjusting the sampling rate adaptively by calculating information metric based on Fisher information and Guassion process regression [10].

Moreover, Lui et al. suggested piecewise linear approximation to compress the sensor readings [11]. Each sensor maintains a fixed size buffer to store the latest sampled data. Once the buffer is full, the node calculates the line segment approximating the original time series. This approach differs from our work as we do not store the sampled data for any extended period of time. Instead, we make a decision on whether to transmit or not immediately after the packets are generated. In [11], the PLAMLiS Algoritm is applied to select samples for transmission which takes polynomial time computation complexity. Our approach is much simpler which takes only constant computation time. Moreover, we will select the data adaptively and forward them along different paths considering the quality-of-information of the sampled data.

III. Quality-of-Information Aware Data Delivery

We present a three-step solution for quality-of-information aware and energy-efficient data delivery which includes 1) Sampling and data selection, 2) Information-aware routing and 3) Data reconstruction.

A. Sampling and Data Selection

An infinite number of samples can be collected from a continuous signal, though this is somewhat physically limited by the hardware on actual systems. On the other hand, it is often unnecessary to oversample since according to Nyquist–Shannon sampling theorem, it is theoretically possible to reconstruct a signal fully if the sampling frequency is greater than twice the maximum frequency of the signal being sampled. If a lower frequency is used, there is possibility that information may be lost and/or there may be problems such as aliasing [8]. The sampling rate hence depends on what events the application is observing. It is important that the application's sampling frequency is high enough so that important events will not be missed between the samples.

After deciding on a sampling rate, a distributed selective transmission algorithm takes the samples and decides whether the data should be transmitted. It is important that the algorithm is simple and computationally inexpensive because the sensors have limited computation power and batteries. In this work, we have designed and implemented a selective transmission algorithm that can be run locally in each node. Our algorithm separates the data into two groups which are 1) routine data and 2) unusual event data based on the exponential moving average (EMA) forecasting method. The method is particularly suitable for environment monitoring applications because they usually have a great proportion of routine data compared with unusual-events data. The routine-data packets are marked as low-priority packets (LP) and the unusual-events data packets are marked as high priority packet (HP) in our approach. Routine data are transmitted selectively and unusual-events data are always transmitted by the sensors. Moreover, HP packets are more important for fast delivery than LP packets, so that our routing protocol will provide better quality of service to the HP packets.

Consider a network with sensors distributed over some open areas or buildings. The sensors take measurements and forward packets containing their measurements to one or multiple sinks. We define $\triangle t$ as the time interval that sensors take measurements from the environment. The value may depend on the capability of the sensors and the minimum frequency to capture the unusual events for a specific application. Let $x_0, x_1, x_2, ..., x_n$ be the sensor readings at time $t_0, t_1, t_2, ..., t_n$, where $t_i = i\triangle t$. The sensor measurement x_i 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 sensor measurement as:

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

where α is constant indicating the weight between the new reading and the old reading. If the difference between the current measurement and the estimated measurement is greater than a threshold ε, i.e. $|x_t - S_t| \geq \varepsilon$, the packet is marked as a HP packet, otherwise, it is marked as a LP packet. It then calculates the sensor measurement deviation, Dev_t, as an estimation of how much x_t typically deviates from S_t by

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

where β indicates the weight between the new reading and the old reading. If Dev_t is greater than the concerned threshold δ, then the data will be reported. Otherwise the routine data is reported only every R_t time intervals, which is measured by a counter C_t. R_t is initially set to 1 then it increases gradually every time if Dev_t is small constantly. It will be set to 1 again if $Dev_t > \delta$. After filtering the data with this algorithm, we then pass the packet with its tag to the information-aware routing protocol that we implemented.

B. Quality-of- Information Aware Routing

Routing protocols generally do not consider the actual data in the packets when they are forwarding them, but they will consider that in QoI-aware routing. From the selective transmission algorithm, the routing protocol is aware of the quality and value of the information in the packets which enables them to make proper routing decisions. The decisions aim at balancing the network traffic and offering paths with shorter delay to more valuable data. We modify the existing SPEED protocol [9] for this purpose.

3.2.1 Priority Queue

Each node will have a queue for buffering the packets in a first in first out (FIFO) manner. Packets may come from two sources, locally generated or arriving from neighboring nodes. Packets from neighboring nodes will be forwarded to the next hop towards the destination. If a packet is marked as a HP packet, there will be an exception invoked in the FIFO queue. The HP packet will preempt all other LP packets in the queue. Consequently, all LP packets are placed at the tail of the queue after all HP packets, so HP packets are always transmitted before the LP packets. This mechanism will allow the HP packets to reach to their destination faster than LP packets since they do not have to wait in the queue for such a long time.

3.2.2 Forwarding

A periodic forwarder is implemented in each node to check the queue length periodically. If it finds a packet in the queue, it adopts the SPEED protocol to select and forward the packet to the next hop. A high priority packet is forwarded to the neighbor with the highest packet travelling speed which is calculated by the advancement to the destination geographically divided by the time taken in forwarding. The next hop for a low priority packet is selected using the probability distribution in the original SPEED protocol [9].

3.2.3 Packet Dropping

If the buffer is full and there are lower priority packets in the queue, a LP packet will be dropped to make space for the HP packet. The HP packets will be dropped only if the buffer is filled with high priority packets only.

3.2.4 Reliable Delivery

Buffer overflow, congestion, contention and transmission errors may all cause packet loss. Existing solutions to these problems usually costly and involving many control messages. Our modified protocol could provide energy-efficient reliable delivery for high priority packets with small overheads.

C. Data Resconstruction

Interpolation and extrapolation are applied to estimate the missing data points at the sinks. There are many Interpolation and extrapolation methods, including linear, polynomial, interpolation using Guassion process, etc. The general idea of these methods is to obtain a function that passes through the exact points of the known dataset. This function can then estimate the unknown data points. Extrapolation is similar to interpolation but is applied for making predictions.

We adopt linear interpolation and exploration for reasons of simplicity and efficiency. Given a set of k data points, i.e. $(x_0,t_0), (x_1,t_1), (x_2,t_2), \ldots, (x_{k-1}, t_{k-1}), (x_{k+1}, t_{k+1})$, where the data at t_k is missing. The missing data denoted by $x(t')$, where $t_{k-1} < t' < t_{k+1}$, can be obtained by the reported data x_{k-1} and x_{k+1} as

$$x(t') = x_{k-1} + (t' - t_{k-1})/(t_{k+1} - t_{k-1})*(x_{k+1} - x_{k-1}).$$

The absolute error $e(t')$ of the reconstructed data at time t' can be measured as

$$e(t') = |r(t') - x(t')|,$$

where $r(t')$ is the real sensing measurement of the environment at time t'.

Extrapolation is applied for constructing the missing data between HP sample and its previous LP sample. The reason to use extrapolation for this region is that it would maintain the trend of the previous packets with a lower average error than interpolation.

In summary, we transmit the data selectively and provide paths with better QoS to HP packets that carrying more important information. We further reconstruct the missing data by simple interpolation and extrapolation techniques.

IV. Experimental Results

We conducted two sets of experiments evaluate our protocol design and implementation. The first experiment is carried out on the Cooja Network Simulator [13]. The second experiment is conducted on the Sensei sensor network testbed [14] with ten Telosb sensor motes in the Wireless Communication Laboratory of Uppsala University.

A. Simulation Results

Simulations are conducted based on the St Bernard deployment [2]. Figure 1 shows the network topology with 18 sensors. The Sink is located at the left bottom corner of the network.

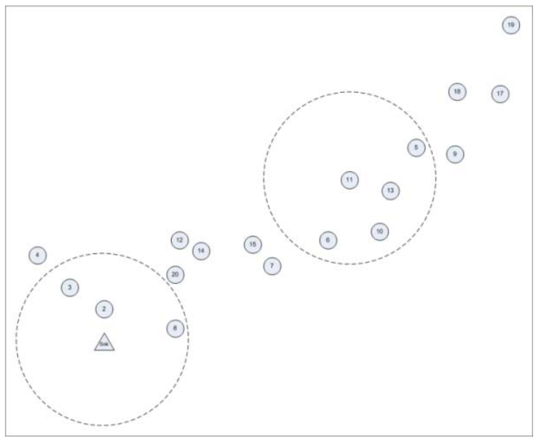

Figure 1. Network Topology of SensorScope

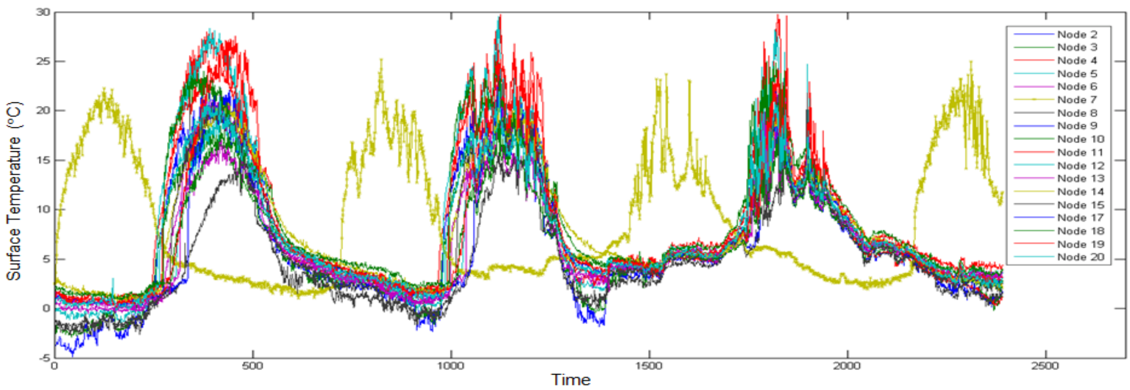

Figure 2. Surface Temperature Plot

Figure 2 is a visualization of the surface temperature of all the nodes. There are three cycles of temperature changes detected by most of the sensors. They occur between the 250th and 600th samples, the 1000th and 1300th samples and the 1700th and 2000th samples. The globally observable change of temperature is likely due to the rise of temperature in the morning and the drop of temperature at night. Note that there is an exception at Node 7. This is because the first 2400 samples from Node 7 started from 9am in the morning of September 21 instead of 12am in the midnight at all the other sensors.

4.1.1 Packet Delivery Rate

Table 1 shows the number of packets received and sent at each node, together with its successful packet delivery rate in the simulation.

	Low Priority Packets (LP)			High Priority Packets (HP)		
Node	Sent	Recv	Success	Sent	Recv	Success
2	1119	1108	99.02%	689	675	97.97%
3	1084	1003	92.53%	638	585	91.69%
4	899	801	89.10%	590	512	86.78%
5	962	813	84.51%	449	350	77.95%
6	1104	982	88.95%	441	377	85.49%
7	917	808	88.11%	672	607	90.33%
8	1164	1124	96.56%	388	375	96.65%
9	941	809	85.97%	426	340	79.81%
10	924	805	87.12%	349	286	81.95%
11	1054	908	86.15%	615	485	78.86%
12	1008	956	94.84%	633	590	93.21%
13	1039	863	83.06%	469	383	81.66%
14	1022	910	89.04%	404	361	89.36%
15	1079	980	90.82%	647	574	88.72%
17	942	755	80.15%	416	339	81.49%
18	942	764	81.10%	416	337	81.01%
19	814	643	78.99%	550	391	71.09%
20	1061	1011	95.29%	440	414	94.09%

Table 1. Successful Data Delivery Rate

The results show that both HP and LP packets can achieve quite high success delivery rate. The success delivery of HP and LP are 86.01% and 88.41% on average which are roughly the same depending on the network traffic.

Our quality-of-information aware data delivery reports the data selectively to reduce the number of messages. Figure 3 shows the message reduction percentage in our approach. The nodes are able to reduce from 25% to 48% of the original messages with our scheme. Note that Node 16 is not functioning, so its data are missing. Consider Node 19 which is around six hops away from the sink, a 43% reduction can save energy considerably since otherwise each message would have been broadcasted for at least 6 times to reach the sink. Our selective transmission algorithm considers is shown to be very effective in reducing the number of message.

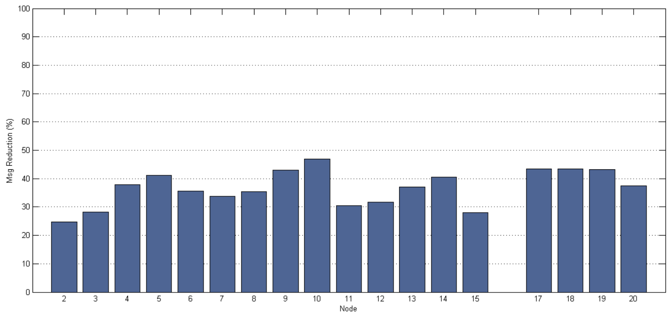

Figure 3. Message Reduction Percentages

4.1.2 Quality-of-Information

We then evaluate the quality-of-information by showing how accurate the reconstructed data are compared with the original samples. Figure 4 shows the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) of each node. There is an inverse correlation between the number of HP packets delivered and the RMSE. The RMSE increases when the HP delivery rate decreases. Node 11 and 19 stand out because they both have delivered very little HP packets.

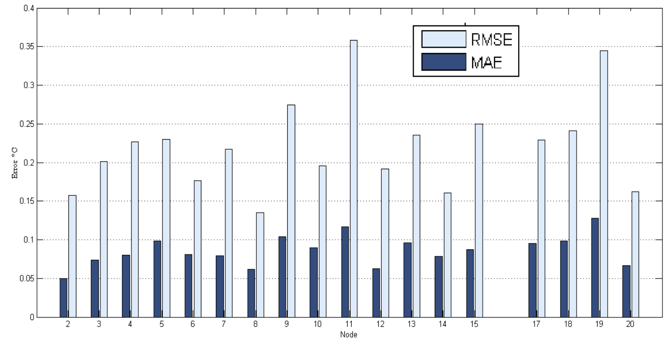

Figure 4. Mean Absolute Error and Root Mean Square Error

We further analyze the distribution of the absolute error from the reconstructed data. The pie chart in Figure 5 shows that up to 94 % of all errors in this simulation are below 0.5ºC, which is obviously tolerable for many temperature monitoring applications.

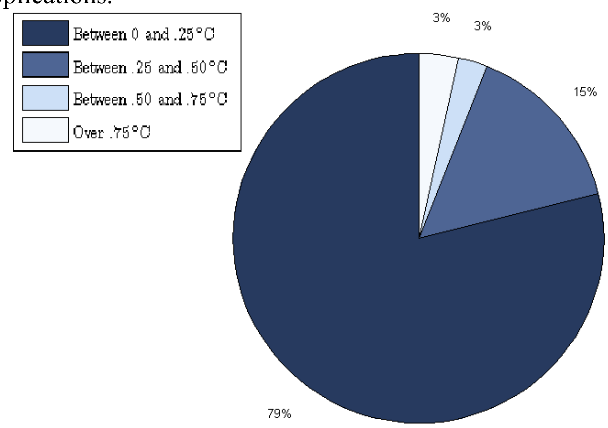

Figure 5. Absolute Error Distribution

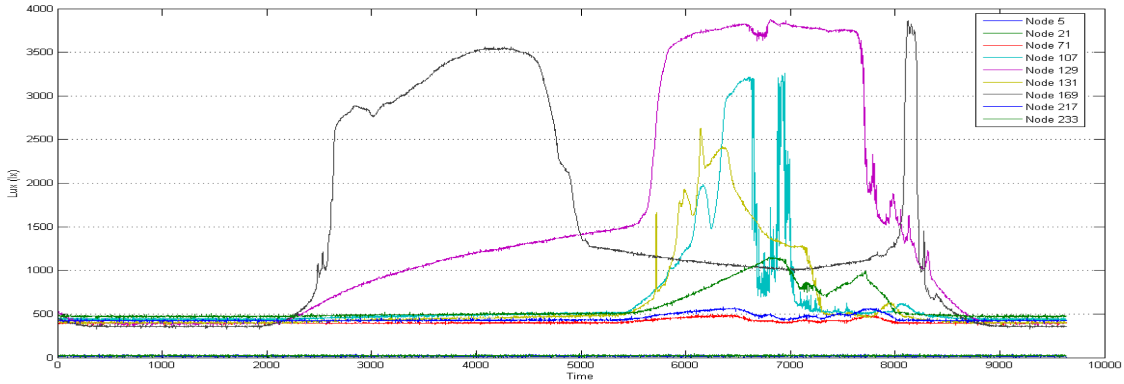

Figure 8. Sampled Light Intensity Data

4.1.3 Average Packet Delay

Figure 6 shows the average packet delay of higher priority and low priority packets from different sensors. Since HP packets are transmitted first in the queue, they can achieve smaller average delay. Packet delay is an important QoI attribute in applications that require fast delivery of HP packets such as in target acquisition systems. The average delay over all the nodes is 764 milliseconds for HP packets and 1021 milliseconds for LP packets.

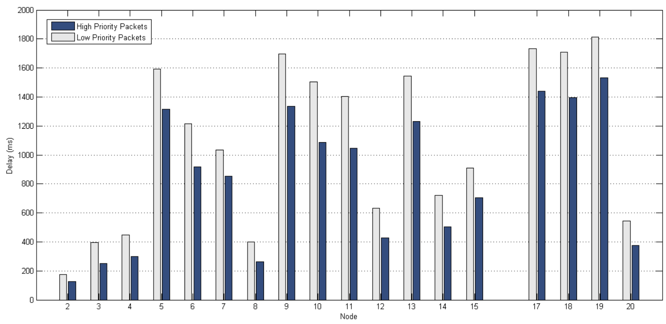

Figure 6. Average Packet Delay

B. *Experimental Results*

In this experiment, we deployed ten TelsoB motes which can measure light intensity on the fourth floor of our office building. Figure 7 is a floor plan showing the IDs and locations of the sensors. One of the sensors acts as the sink here which is labeled as SNK. The light intensity sensors use a ceramic package that is light impervious, so no stray light can reach the active area from the side or from the backside of the sensors. The settings allow reliable optical measurements to be taken in the visible to near infrared range over a wide and dynamic range of light intensity. The experiment was conducted from 10pm on May 30, 2009 to 1am on June 1, 2009. Each sensor runs Contiki [4] with a queue implemented on top of Contiki's single packet Rime buffer. All of the sensors take samples every 10 seconds.

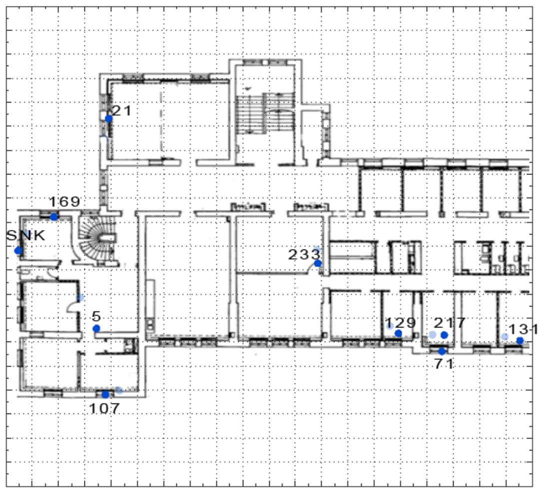

Figure 7. Testbed Floorplan

Figure 8 shows the data sampled by the sensors on our floor. The sensors that give very low readings of light intensity are those sensors located in some dark corners in the building. Only the sensors which are close to the natural light give great variations in their readings.

4.2.1 Packet Delivery Rate

Table 2 shows the number of packets sent and received by each node as well as their successful packet delivery rate. Several sensors, namely 5, 21, 71, 217 & 233, did not observe any important event. This means that the light intensity did not change more that 122 lux from time to time at these locations.

Figure 9 shows the results of message reduction percentages. Due to the smoothness of the collected data, we are able to achieve very high message reduction percentages, such as 98.6% in Node 5 and over 85% for the remaining sensors in our application. It indicates that the percentages of message reduced depend very much on the application itself, the environment and the characteristic of the data.

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Node	Low Priority Packets (LP)			High Priority Packets (HP)		
	Sent	Recv	Success rate	Sent	Recv	Success rate
5	135	132	97.78%	0	0	-
21	233	230	98.71%	0	0	-
71	348	284	81.61%	0	0	-
107	1165	1149	98.63%	191	186	97.38%
129	1170	1079	92.22%	31	30	96.77%
131	1017	778	76.50%	27	26	96.30%
169	1124	1124	100%	87	87	100%
217	489	459	93.87%	0	0	-
233	699	676	96.71%	0	0	-

Table 2. Error and Delivery Statistics

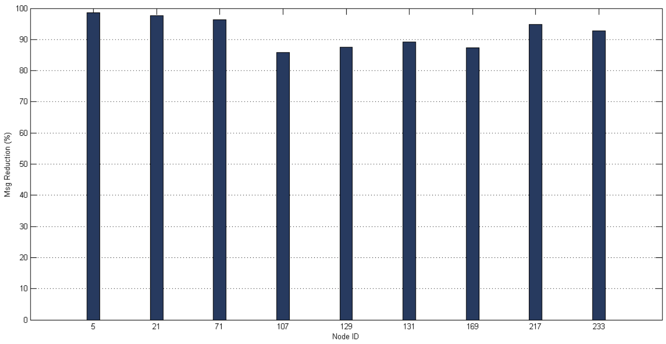

Figure 9. Message Reductions Percentages

4.2.2 Quality-of-Information

Figure 10 shows the MAE and RMSE from the data that the sink has reconstructed. It indicates that the sensors can achieve very low errors in our light intensity monitoring application.

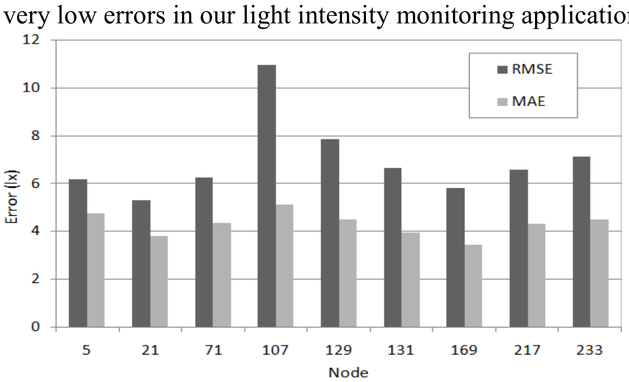

Figure 10. Mean Absolute Error and Root Mean Square Error

V. CONCLUSION

We proposed a quality-of-information aware and energy-efficient data delivery framework for wireless sensor networks. We focus on two aspects of quality-of-information in this work, including the data accuracy and timeliness. Packets carrying important information are reported with high priority and along paths with lower packet delays. On the contrary, the remaining routine data are reported only selectively to reduce the network traffic and energy consumption. We conducted extensive experiments with real sensing data from a temperature monitoring application and implemented a sensor network testbed with light intensity sensors to evaluate the performance of our proposed data delivery service. Both experimental results show that our scheme can provide high quality-of-information, in terms of high data accuracy and low packet delay, and greatly reduce the communication overheads.

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