An Adaptive Transmission Rate Control Approach to Minimize Energy Consumption

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***Abstract*—There is a tradeoff between energy saving and real-time stream deadline meeting in wireless sensor transmission. Existing work has proposed rate control methods to minimize energy consumption based on several ideal assumptions, e.g., a packet arriving earlier has an earlier deadline, packet arrival times are known precisely, and a packet transmission can be preempted. We remove these unrealistic assumptions and propose an online rate control approach that adjusts transmission rates efficiently to minimize energy dissipation. Preliminary results indicate that our method greatly improves existing approaches.**

I. Introduction

Wireless sensor network is widely used in cyber-physical applications, such as the health care and environment monitoring (e.g. [13], [17]). Most of the wireless sensors are powered by batteries and store a limited amount of energy, hence require the transmission to be energy efficient. Lower transmission rates can greatly reduce transmission energy. However, if the lowest transmission rate is selected, many messages could miss their deadlines, which degrades the quality of service (QoS) for real-time applications. Therefore, it is important to design an efficient approach for adjusting transmission rates in order to not only achieve energy saving, but also maximize the QoS.

There are some recent publications on the transmission rate adjustment to minimize energy dissipation while still satisfying the timing requirement of real-time streams under earliest deadline first (EDF) scheduling. Some papers, [18], [20] and [6], propose optimal approaches, by assuming a given amount of data needed to be transmitted within an absolute deadline, to minimize the energy consumption and maximize the data throughput, respectively. The works of [5], [16] assume that all packets to be transmitted have a common absolute deadline. The situation considered in these papers, cannot be directly applied to handle cases where different packets have different absolute deadlines. There are works selecting rates for packets based on that each packet has its own absolute deadline. Some of these, e.g., [4], [9], [21], assume that the energy function for all the packets are the same, while other more general approaches, e.g., [15], [22] are proposed based on the fact that the energy functions are influenced by the fading channel state, transmission distance, and so on. All of these works assume that a packet arriving earlier always has an earlier deadline. Furthermore, some of the above approaches [4], [5], [16], [21] assume that the arrival times of future packets are known apriori precisely, and others [6], [18], [20], [21], assume that a packet transmission can be preempted at arbitrary timing during transmission, neither of which are realistic in wireless sensor networks. Moreover, the algorithms proposed by [6], [15] is extremely time consuming.

In addition to the study of the rate control in wireless sensor networks, there is also much research work on dynamic voltage frequency scaling (DVFS), which is similar to the rate control in sensor nodes. Some papers, e.g., [10], [11], [19], propose CPU speed selection approaches for a set of preemptive jobs. The preemptive execution of CPU jobs does not map well to packet transmission in wireless sensor networks. The work in [8] proposes a CPU speed slow down method for periodic tasks that have maximum blocking times. However, the schedulability condition [1], [2], [12] employed in this paper [8] is not only pessimistic, but also time consuming. A busy period decomposition method is proposed in [14] for a set of non-preemptive jobs based on the assumption that a job arriving earlier always has an earlier deadline. All of the proposed approaches know the release times of jobs exactly, which is unrealistic in wireless sensor networks.

In this paper, we propose an online transmission rate selection approach based on an optimal dynamic voltage frequency scaling algorithm Lp-EDF [19]. Our approach exploits the periodicity property of the real-time streams to predict the future jobs' timing information and find an optimal transmission rate schedule. We are designing our approach to make more messages meet their deadlines. Preliminary results show that our approach achieves a higher success ratio with a lower timing cost compared with existing works, although the energy dissipation caused by our approach sees a small increase.

II. Preliminaries

We consider a system composed of a set of streams $\{S_i\} = \{S_1, S_2, ..., S_N\}$. Stream S_i periodically generates a message of C_i bytes with a period T_i. The message generated at time $R_{ij} = O_i + (j-1) \cdot T_i - J_{ij}$ is denoted as M_{ij}, where O_i is the release offset of the stream S_i and J_{ij} is the jitter of the message arrivals. We assume that the jitter satisfies a uniform distribution $J_{ij} \sim U(0, T_i)$. Each message M_{ij} has a relative deadline D_i, and its absolute deadline $AD_{ij} = O_i + (j-1) \cdot T_i + D_i - J_{ij}$. According to [7], the fragmentation threshold $Threshold$ is the maximum non-preemption length of each message. Each message M_{ij} is fragmented to $X_i = \lceil \frac{C_i}{Threshold} \rceil$ packets, and the first $X_i - 1$ packets and the last packet have the length $Threshold$ and $C_i - (X_i - 1) \cdot Threshold$, respectively. Similar to 802.11a [7], before a node transmits a packet, it needs $Overhead\_Time$ time to transmit the preamble and the "Signal" part of the PLCP header. Then, the "Service" part of the PLCP header, with its size $PLCP\_Length$, will be transmitted with the payload. Based on these definitions, we define the intensity $g(I)$ of a time interval $I = [t, t']$ to be,

$$g(I) = \frac{\sum_{i=1}^{N} Y_i \cdot (C_i + X_i \cdot PLCP\_Length)}{t' - t - \sum_{i=1}^{N} Y_i \cdot X_i \cdot Overhead\_Time}, \quad (1)$$

where Y_i is the number of messages with $[R_{ij}, AD_{ij}] \subseteq I$.

We consider a single wireless sensor node which has transmission rate r, which can take on any value in $[min\_rate, max\_rate]$, where min_rate and max_rate are the minimum and maximum allowed rates for the node, respectively. The wireless node handles the given set of streams $\{S_i\}$. The transmission power P is a convex function of the transmission rate according to [16]. In this paper, we assume that the transmission power function is,

$$P(r(t)) = max\_rate \cdot Noise \cdot L^2 (2^{\frac{2 \cdot r(t)}{max\_rate}} - 1), \quad (2)$$

where L is the transmission distance and $Noise$ is the noise power according to [22]. The packets of the streams are stored in a buffer, whose size is $MaxSize$.

We refer to $[R_{ij}, AD_{ij}]$ as the active interval of the message M_{ij}. A schedule $S(t_0, t_1)$ is a pair of $(r(t), Message(t))$ functions defined over the given time interval $[t_0, t_1]$, where $Message(t)$ defines the message being transmitted at time t with rate r(t) (or idle if $r(t) = 0$). The total energy consumed during a given time interval $[t_0, t_1]$ is

$$E(S) = \int_{t_0}^{t_1} P(r(t))dt. \quad (3)$$

The goal of our scheduling problem is to find a feasible schedule that minimizes the transmission energy, while the following constraint is satisfied for any message whose interval is within the time interval $[t_0, t_1]$,

$$\int_{R_{ij}}^{AD_{ij}} r(t)\delta(Message(t), M_{ij})dt = C_i,$$
$$\forall M_{ij}, [R_{ij}, D_{ij}] \subseteq [t_0, t_1], \quad (4)$$

where $\delta(Message(t), M_{ij}) = 1$ if $Message(t) = M_{ij}$ and 0 otherwise. To make all the messages reach their destinations within their deadlines, the constraint (4) should be satisfied for any message. However, in wireless sensor networks, the jitters of the message arrivals, the non-preemption property of a packet, and the dynamic interference in the transmission environment will cause some of the messages miss their deadlines inevitably. We define the message success ratio SR within a given time interval to be

$$SR = \frac{Num\_Message\_Sucess}{Num\_Message}, \quad (5)$$

where $Num\_Message$ is the number of transmitted messages within the time interval, while $Num\_Message\_Sucess$ is the number of messages successfully delivered within the deadlines. Message success ratio SR represents the percentage of the messages that satisfy constraint (4) within a given time interval if we assume that the impact of interference has been adequately handled by the rate assignment.

Our problem is to find rates for the messages to be transmitted within a given time interval, in order to not only minimize the transmission energy (3), but also to make as many messages as possible to satisfy the schedulability constraint (4). To accomplish this, we need an adaptive rate control approach that is able to adjust the rates efficiently in response to the jitters of the message arrivals, and effectively reduce the influence of the packet non-preemption property on the success ratio. Specifically, when a new message arrives at the buffer at time t_0, we have

$$\min_{r(t)} \int_{t_0}^{t_1} P(r(t))dt \quad (6)$$

$$\text{s.t.} \int_{R_{ij}}^{AD_{ij}} r(t)\delta(Message(t), M_{ij})dt = C_i,$$
$$\forall M_{ij}, [R_{ij}, D_{ij}] \subseteq [t_0, t_1], \quad (7)$$

where t_0 is the current time, i.e., the release time of the new message, and t_1 is set to be $\max_{M_{ij}|R_{ij} \le t_0}\{AD_{ij}\}$.

We use EDF scheduling algorithm since it is optimal in scheduling a set of periodic streams on a single sensor node. An optimal minimum energy scheduler Lp-EDF is proposed in [19] under preemptive EDF scheduling. Though Lp-EDF was originally for scheduling CPU tasks, it can be modified to schedule messages in wireless sensor networks, where messages are fragmented to non-preemptive packets and message arrival times are not known precisely.

III. OUR APPROACH

Our problem is to find message transmission rates within a given time interval such that the transmission energy is minimized and the transmission success ratio is as high as possible. We solve the problem by an online approach so as to better respond to dynamic variations including arrival time jitters, failed delivery, etc. An outline of our approach is as follows. Every time a new message arrives at the buffer, the sensor node will compute the rates for the messages in the buffer by solving an optimization problem as given in (6) and (7). If a packet is being transmitted upon the arrival of a new message, the node will finish the transmission of this packet before computing a new schedule. To make the online approach work well, we need to address issues including prediction of future load and solving the resulting optimization problem. With the predicted packets and the packets already in the buffer, solving the optimization problem defined in (6) and (7) can employ the Lp-EDF algorithm introduced in [19].

Since future messages may compete for the time resource with the messages already in the buffer and greatly influence the transmission success ratio and the energy consumption, it is necessary to predict the future messages that release within some time window. We define the time interval $[t_0, \max_{M_{ij}|R_{ij} \le t_0}\{AD_{ij}\}]$ as the scheduling window W at

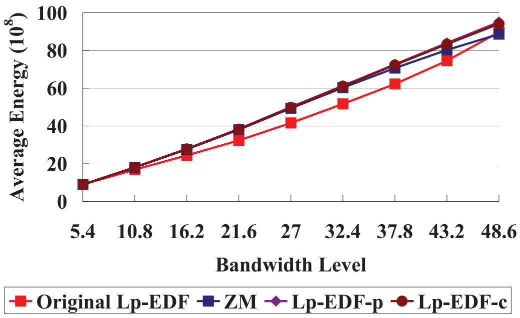

Fig. 1. Comparison of original Lp-EDF, ZM, Lp-EDF-p and Lp-EDF-c in terms of average success ratio.

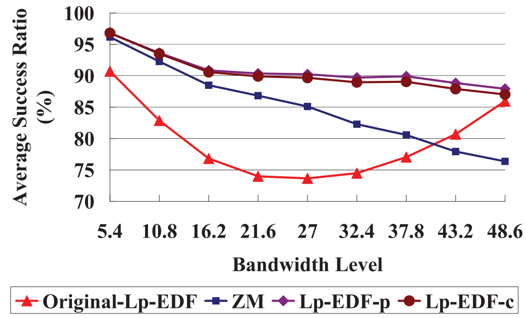

Fig. 2. Comparison of original Lp-EDF, ZM, Lp-EDF-p and Lp-EDF-c in terms of energy consumption.

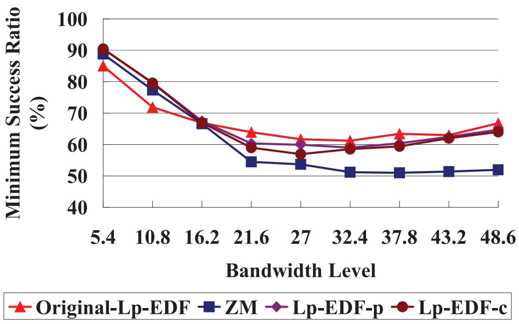

Fig. 3. Comparison of original Lp-EDF, ZM, Lp-EDF-p and Lp-EDF-c in terms of average success ratio.

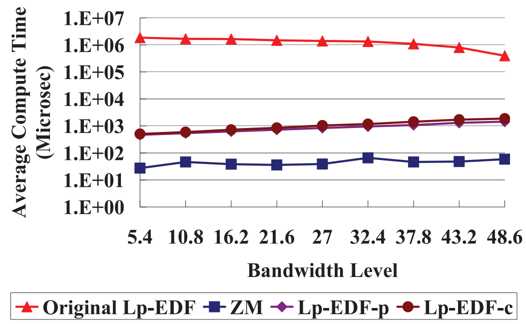

Fig. 4. Comparison of original Lp-EDF, ZM, Lp-EDF-p and Lp-EDF-c in terms of energy consumption.

time t_0. When computing the transmission rates at time t_0, the node considers not only the messages M_{ij} already in the buffer, but also the future messages M_{km} whose release time R_{km} is larger than t_0 but smaller than $\max_{M_{ij}|R_{ij} \le t_0}\{AD_{ij}\}$.

We consider two ways to predict the future messages. The first one is called **proportional prediction** (Lp-EDF-p). If the absolute deadline AD_{km} of a predicted message M_{km} is within the window W, we include message as is. However, if $AD_{km} > \max_{M_{ij}|R_{ij} \le t_0}\{AD_{ij}\}$, we modify the message size and deadline to C'_k and AD'_{km}, where $C'_k = C_k \cdot \frac{\max_{M_{ij}|R_{ij} \le t_0}\{AD_{ij}\} - R_{km}}{AD_{km} - R_{km}}$ and $AD'_{km} = \max_{M_{ij}|R_{ij} \le t_0}\{AD_{ij}\}$, respectively. The packet number X'_k under this schedule computation is equal to $\lceil \frac{C'_k}{Threshold} \rceil$. The other way is to treat the future message M_{km} with AD_{km} beyond the window W by the same way as treating the messages whose absolute deadlines are within the window W, which is called **complete prediction** (Lp-EDF-c). Any future message M_{km} with its release time within the window W has the message size C_k and absolute deadline AD_{km}.

The improved Lp-EDF algorithm identifies a critical interval $I^* = [t', t'']$ whose intensity $g(I^*)$ is maximum within the time interval $[t_0, t_1]$. We incorporate the timing overhead of the packet transmission, such as the preamble and the PLCP header, into the intensity computation as shown in (1). Then, the rates r of the messages are set to be $g(I^*)$ if their release times and absolute deadlines are within the critical interval I^*, and these messages are deleted from the message set. This process is repeated until all the messages obtain their rates.

IV. Preliminary Results

We evaluate the performance and efficiency of our proposed online approach on randomly generated stream sets and compare the modified Lp-EDF approach, both Lp-EDF-p and Lp-EDF-c, with the original Lp-EDF and ZM algorithm in [21]. Our modified Lp-EDF algorithm was implemented in C++, running on an AMD Phenom(tm) II X4 940 workstation with Red Hat Enterprise Linux 4. 1000 stream sets consisting of 5 streams each were randomly generated for 9 different bandwidth levels ($Bandwidth_{level} = 0.1Mbps, ..., 0.9Mbps$) with a total of 9000 stream sets. The bandwidth level is defined to be $Bandwidth_{level_i} = \sum_{j=1}^{5} \frac{C_j}{T_j}, i = 0.1, ..., 0.9$. We employ IEEE 802.11a [7] as the MAC protocol, which has the minimum and maximum rates as $6Mbps$ and $54Mbps$, respectively. To fully show different performance of the stream sets at different bandwidth levels in 802.11a, we multiply the message length of each stream by 54 times, and change the bandwidth levels to be $5.4Mbps, ..., 48.6Mbps$. In addition, the fragmentation threshold $Threshold$, the overhead time $Overhead\_Time$ and the length of PLCP header $PLCP\_length$ are set to be 2346 bytes, 40 μs, and 2 bytes, respectively. We assume that the stream S_i with the highest density $\frac{C_i}{D_i}$ in a stream set releases its messages with jitter J_{ij}, which satisfies a uniform distribution $J_{ij} \sim U(0, T_i)$. For the details of the stream set generation, readers can refer to [3].

Although Lp-EDF is optimal under preemptive EDF, its computation time is extremely long because of its time complexity $O(NUM^3)$ for NUM messages. In addition, the performance of Lp-EDF is negatively influenced by the jitters of the messages and the packet non-preemption property.

Another energy minimization scheduling algorithm, denoted as ZM, presented in [21], dynamically computes the lowest rate for the messages to minimize the energy consumption. There are two disadvantages of ZM. First, ZM is not optimal when a message arriving later has an earlier deadline. Second, ZM suffers less but still obviously from the jitters of message arrivals and packet non-preemption property.

In the first experiment, we compare energy consumption resulted from applying the original Lp-EDF, ZM and our approach, as shown in Figure 1. The x-axis represents the bandwidth level, while the y-axis represents the average energy consumption per stream set. It is illustrated that the original Lp-EDF performs a little better than our approach and ZM in energy saving, while our approach achieves the energy saving comparable with that of ZM at all bandwidth levels.

The second experiment shows the average success ratio obtained by the original Lp-EDF, ZM, and our approach in Figure 2. The x-axis shows the bandwidth level, whereas the y-axis represents the average success ratio, which is the percentage of the successfully transmitted messages among the 1000 stream sets at each bandwidth level. First, the average success ratios resulted from the original Lp-EDF are much lower than the results by our approach at bandwidth levels $5.4Mbps$ to $43.2Mbps$, because the original Lp-EDF statically computes all the rates for the whole time interval under preemptive EDF and neglects the message jitters. Second, for bandwidth levels greater than $16.2Mbps$, the performance of ZM degrades drastically, because ZM cannot handle the case that a message arriving later has an earlier deadline, which appears frequently when bandwidth levels become higher.

To further compare the performance of different approaches, the minimum success ratio among the 1000 stream sets at each bandwidth level is shown in Figure 3. The x-axis represents the bandwidth level, while the y-axis represents the minimum success ratio. For the bandwidth levels less than or equal to $16.2Mbps$, the minimum success ratios by ZM are a little lower than those obtained by our approach, while for bandwidth levels greater than $16.2Mbps$, the minimum success ratios resulted by ZM are much lower than those obtained by our approach. In contrast, for bandwidth levels $21.6Mbps$ to $48.6Mbps$, the minimum success ratios by the original Lp-EDF are a little higher than those by our approach.

We study the average computation time of a stream set by our approach and compare them with the original Lp-EDF and ZM in the third experiment, as shown in Figure 4. The x-axis represents the bandwidth level, while the y-axis represents the average rate computation time. As shown in Figure 4, our method runs 200 to 4000 times faster than the original Lp-EDF, while it is 10 to 36 times slower than the ZM algorithm.

Based on the preliminary results, our approach can achieve much higher success ratios on average than the original Lp-EDF and ZM, though the energy dissipation by applying our approach sees a small increase compared with the original Lp-EDF. Furthermore, the computational cost of our approach is significantly smaller than that of the original Lp-EDF. ZM takes less time than our approach to compute the rates, but its success ratios are not satisfactory at high bandwidth levels.

V. Summary and Future Work

We have presented an online transmission rate control approach to minimize energy dissipation while still guaranteeing deadline requirement of real-time streams in wireless sensor networks. Our approach is based on several assumptions, i.e., each packet has its own deadline, the arrival times of messages are unknown apriori precisely, and a packet transmission cannot be preempted. Our approach formulates the rate control problem as an optimization problem and solves it by improving the original Lp-EDF algorithm. Preliminary results show that our approach works excellently in energy saving and deadline meeting with a low timing cost. We are improving our approach to make more messages meet deadlines and speed up our algorithm. We will implement our approach in a testbed, and compare it with existing methods.

References

[1] S. K. Baruah, L. E. Rosier, and R. R. Howell, "Algorithms and complexity concerning the preemptive scheduling of periodic, real-time tasks on one processor," *Real-Time Syst.*, vol. 2, no. 4, 1990.

[2] G. C. Buttazzo, "Hard real-time computing systems: Predictable scheduling algorithms and applications." Springer, 2005.

[3] T. Chantem, X. S. Hu, and M. Lemmon, "Generalized elastic scheduling for real-time tasks," *IEEE Trans. Comput.*, 2009.

[4] W. Chen, M. Neely, and U. Mitra, "Energy-efficient transmissions with individual packet delay constraints," *IEEE Trans. Inf. Theory*, 2008.

[5] A. El Gamal, C. Nair, B. Prabhakar, E. Uysal-Biyikoglu, and S. Zahedi, "Energy-efficient scheduling of packet transmissions over wireless networks," in *INFOCOM*, 2002.

[6] A. Fu, E. Modiano, and J. Tsitsiklis, in *INFOCOM*, 2003.

[7] M. S. Gast, "802.11@wireless networks: The definitive guide creating and administering wireless networks," in *O'REILLY*, 2002.

[8] R. Jejurikar and R. Gupta, "Energy-aware task scheduling with task synchronization for embedded real-time systems," *IEEE Trans. Comput.-Aided Design Integr. Circuits Syst.*, 2006.

[9] M. Khojastepour and A. Sabharwal, "Delay-constrained scheduling: power efficiency, filter design, and bounds," in *INFOCOM*, 2004.

[10] W.-C. Kwon and T. Kim, "Optimal voltage allocation techniques for dynamically variable voltage processors," *ACM Trans. Embed. Comput. Syst.*, vol. 4, 2005.

[11] M. Li and F. F. Yao, "An efficient algorithm for computing optimal discrete voltage schedules," *SIAM J. Comput.*, vol. 35, 2005.

[12] J. W. Liu, "Real-time systems." Prentice Hall, 2000.

[13] G. Loandpez, V. Custodio, and J. Moreno, "Lobin: E-textile and wireless-sensor-network-based platform for healthcare monitoring in future hospital environments," *IEEE Trans. Inf. Technol. Biomed.*, 2010.

[14] J. Mao, C. G. Cassandras, and Q. Zhao, "Optimal dynamic voltage scaling in energy-limited nonpreemptive systems with real-time constraints," *IEEE Trans. Mobile Comput.*, 2007.

[15] L. Miao and C. G. Cassandras, "Optimal transmission scheduling for energy-efficient wireless networks," in *INFOCOM*, 2006.

[16] B. Prabhakar, E. Uysal Biyikoglu, and A. El Gamal, "Energy-efficient transmission over a wireless link via lazy packet scheduling," in *INFOCOM*, 2001.

[17] W.-Z. Song, R. Huang, M. Xu, B. Shirazi, and R. LaHusen, "Design and deployment of sensor network for real-time high-fidelity volcano monitoring," *IEEE Trans. Parallel Distrib. Syst.*, 2010.

[18] A. Tarello, J. Sun, M. Zafer, and E. Modiano, "Minimum energy transmission scheduling subject to deadline constraints," in *WIOPT*, 2005.

[19] F. Yao, A. Demers, and S. Shenker, "A scheduling model for reduced cpu energy," in *FOCS*, 1995.

[20] M. Zafer and E. Modiano, "Optimal adaptive data transmission over a fading channel with deadline and power constraints," in *INFOCOM*, 2006.

[21] ——, "A calculus approach to energy-efficient data transmission with quality-of-service constraints," *IEEE/ACM Trans. Netw.*, 2009.

[22] X. Zhong and C.-Z. Xu, "Online energy efficient packet scheduling with delay constraints in wireless networks," in *INFOCOM*, 2008.