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A Multi-queue Approach of Energy Efficient Task Scheduling for Sensor Hubs

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Abstract — With the emergence of Internet of things (IoT), sensor hubs, which integrate data from different sensors, play increasingly important role. Energy efficiency is one of the most important issues for sensor hubs. To attack this challenge, this paper proposes a task scheduling scheme for sensor hubs to improve their energy efficiency. A multi-queue-based framework is designed, and its theoretical model and the corresponding mathematical analyses are presented. By optimizing the model with Lyapunov optimization techniques, an algorithm of energy efficient task scheduling in sensor hubs is proposed. Finally, simulation experiments based on real-life data extracted from Internet of vehicles (IoV) environments are conducted to validate the efficacy of the approach.

Key words — Internet of things (IoT), Sensor hub, Energy efficiency, Task scheduling, Queueing model.

I. Introduction

With the emergence of Internet of things (IoT), the number of sensors increases exponentially. It has been reported that the number of connected devices has reached 9 billion in 2012[1], and such number is predicted to increase to 75 billion in the year of 2020[2]. In order to efficiently connect and manage the sensors or devices, sensor hubs are designed and deployed to integrate data from different sensors. Such technology is able to off-load the tasks from the sensors, hence saving energy consumption and providing a performance enhancement. Sensor hubs have been widely applied in reality, from personal smart phones (*e.g.*, Apple iPhone, Google Nexus) to large-scale IoT systems.

Typically, there are several sensing devices connected to a sensor hub. In the sensor hub, data from the sensors is firstly buffered and waiting for further processing by the Microcontroller unit (MCU) until a certain amount of data has been accumulated in the buffer[3]. The sensing data can be processed in batch by the sensor hub or uploaded to the servers connected to the sensor hub.

With the increase of sensors and sensor hubs in reality, energy efficiency has become an important issue[4,5]. Some of the sensor hubs are powered by embedded battery, which requires low battery consumption with high processing efficiency. Besides integrating sensor data synchronously, sensor hubs are able to reduce the energy consumption by powering themselves down when idle[6]. However, how to determine the working status of the sensor hubs dynamically according to the workload in order to achieve the trade-off between performance stability and energy consumption remains largely unexplored.

To tackle this challenge, this paper studies the energy efficient task scheduling problem in sensor hubs from both theoretical and practical aspects. Theoretically, quantitative analysis of queue stability and energy efficiency in sensor hubs is conducted, and the task scheduling is formulated by a stochastic optimization problem. Lyapunov optimization technique is applied, and quantitative analysis is provided to prove the optimality. Practically, an approach with multiple queues is proposed, and task scheduling algorithm is designed and implemented. The effectiveness of the approach is validated by experimental results with real-world dataset.

The remainder of this paper is organized as follows. Section II introduces the background and related work most pertinent to this paper. In Section III, we formulate the processing procedures of sensor hubs by queueing model, and present the mathematical model of energy efficient task scheduling. In Section IV, we optimize the

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model with Lyapunov optimization technique, and design detailed algorithm of energy efficient task scheduling for sensor hubs. Then we validate the efficacy of our scheme experimentally based on real-world data in Section V. Finally, we conclude the paper in Section VI.

II. Background and Related Work

Energy efficiency has always been an important issue in Wireless sensor network (WSN). Song *et al.*[7] proposed a minimum energy scheduling algorithm for multi-hop wireless networks with stochastic traffic arrivals and time-varying channel conditions. Tang *et al.*[8] studied the tradeoff between energy conservation and user fairness, and proposed a three-stage joint power control and channel assignment mechanism for Device-to-device (D2D) communication. Tunca *et al.*[9] presented a distributed mobile sink routing protocol for time-sensitive applications in WSN, aiming to minimize the overhead while preserving the advantages of mobile sinks. Dai *et al.*[10] dealt with the energy efficiency problem from MAC layer, and designed an energy efficient MAC protocol for Linear WSN. Song and Zheng[11] formulated the energy efficiency problem in wireless powered sensor network as a nonlinear fractional programming, and designed a particle-swarm-optimization-based solution algorithm. Guo *et al.*[12] studied the tradeoff between energy harvesting and data forwarding in WSN, and proposed a resource allocation algorithm by considering different power splitting abilities of relays. Rout and Ghosh[13] attempted to improve the energy efficiency of the bottleneck zone in a WSN by combining duty cycle and network coding. Yan *et al.*[14] studied the energy efficiency issue of compressed sensing in WSN, and proposed an optimal compressed data gathering framework and its corresponding algorithm. Chen *et al.*[15] designed a scheme of task offloading and frequency scaling for mobile devices in mobile edge computing environments in order to improve their energy efficiency.

However, there has been less attention paid to the energy efficiency issue of sensor hubs. With the growing popularity of sensor hubs in IoT, such issue should be addressed properly for extending the lifetime of the devices and reducing energy consumption. To this end, we try to improve the energy efficiency of sensor hubs by designing a task scheduling scheme which is able to dynamically adjust the working status of the sensor hubs according to its workload in order to achieve optimal trade-off between performance stability and energy consumption.

Since all of the sensor hubs are equipped with a buffer or multiple buffers, we make full use of them to design the task scheduling approach. We construct several queues with the buffer(s), and study their task arrivals, buffering, and status control. The basic scenario is illustrated by Fig.1.

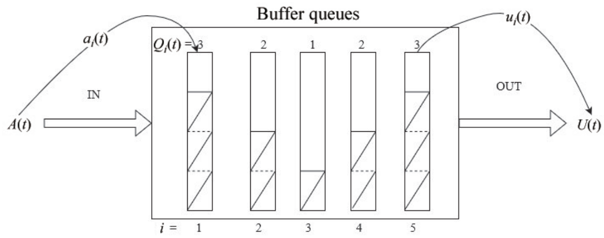

Fig. 1. Task scheduling with multiple queues

The notations and definitions used in the following parts of this paper are shown in Table 1.

Table 1. Notations and definitions

Notation	Definition
I	Number of queues in the sensor hub
Mem	Buffer size of each queue
$Q_i(t)$	Number of requests buffered in the i-th queue
$A(t)$	Number of requests arrived at the sensor hub in the interval from $t-1$ to t
$a_i(t)$	Number of requests arrived at the i-th queue in the interval from $t-1$ to t
$u_i(t)$	Number of requests uploaded by the i-th queue in the interval from $t-1$ to t
$U(t)$	Upper bound of upload requests in the interval from $t-1$ to t
$p(t)$	Power consumption in the interval from $t-1$ to t
$R(t)$	Reward obtained in the interval from $t-1$ to t

III. Model of Sensor Hub and Task Scheduling

1. Queueing model of sensor hub

The tasks arrived at a sensor hub will be distributed into different queues. We suppose that $a_i(t)$ is the number of tasks that arrive at the i-th queue in the interval from $t-1$ to t, and $A(t)$ denotes the total number of tasks arrived at the sensor hub. We let $Q_i(t)$ express the state of the i-th queue which is the number of requests buffered in such queue, and Mem denote the buffer size. Therefore, we have the following inequalities.

$$\sum_{i=1}^{I} a_i(t) \le A(t) \tag{1}$$

$$a_i(t) \le Mem - Q_i(t) \tag{2}$$

At each decision epoch, our scheme controls the working status of the sensor hub, which determines the amount of data submitted or processed in each queue. Let $u_i(t)$ denote the number of requests uploaded or processed at the i-th queue in the interval from $t-1$ to t, and $U(t)$ be the upper bound of upload requests in the interval at the current status. Therefore, for the departure procedures of the queues, we have the following inequalities.

$$u_i(t) \le Q_i(t) \tag{3}$$

$$\sum_{i=1}^{I} u_i(t) \le U(t) \tag{4}$$

With Eqs.(1)–(4), we have the formulation of the queue dynamics expressed as Eq.(5). Mathematically, the state of the i-th queue is updated at each decision epoch by jointly considering its previous state, task arrivals, and workload departures.

$$Q_i(t+1) = \max[Q_i(t) + a_i(t) - u_i(t), 0] \tag{5}$$

In order to guarantee the stability of the queues, the status of each queue in steady state (when t goes to infinity) should be bounded. Theoretically, such stability constrain is expressed as follows.

$$\lim_{T\to\infty} \frac{1}{T}\mathbf{E}[Q_i(T)] = 0, \quad i \in \{1, \cdots, I\} \tag{6}$$

2. Optimization model of task scheduling

In order to optimize the energy efficiency of the sensor hub, we firstly define the transient reward $R(t)$ in the time interval from t to $t+1$. The reward is defined by the summation of the utility functions with the value of the task arrivals divided by the power consumption. The expression of the transient reward $R(t)$ is illustrated by Eq.(7).

$$R(t) = \sum_{i=1}^{I} a_i(t)/p(t) \le A(t)/p(t) \tag{7}$$

For improving the energy efficiency in a sensor hub, by properly setting the power status, task distributions among the queues, and the departure rate of each queue, the objective is to optimize the long-time reward of the system. In other words, the reward of the sensor hub is expected to be maximized in steady state (*i.e.*, when t goes to infinity). Meanwhile, the stability of the queue should be satisfied, as well as all the inequalities of the queueing model. In summary, the mathematical optimization model of energy efficient task scheduling for a sensor hub is expressed as follows.

$$\max_{p(t),a_i(t),u_i(t)} f = \lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1}\mathbf{E}[R(t)] \tag{8}$$

s.t. Eqs.(1), (2), (3), (4), and (6)

IV. Algorithm of Task Scheduling

1. Solving the optimization problem

In order to solve the optimization problem presented in the previous section, we introduce Lyapunov optimization technique. To facilitate the following procedures, we define $\Theta(t)$ as the vector of queue states expressed as Eq.(9), and the Lyapunov function denoted by $L(\Theta(t))$ as Eq.(10) illustrating the congestion state of the queues.

$$\Theta(t) \equiv [Q_1(t), Q_2(t), \cdots, Q_I(t)] \tag{9}$$

$$L(\Theta(t)) = \frac{1}{2}\sum_{i=1}^{I} Q_i^2(t) \tag{10}$$

Next, we define the conditional Lyapunov drift $\Delta(\Theta(t))$ by Eq.(11), and the drift-minus-reward function expressed by Eq.(12) where V is a non-negative weight on the reward.

$$\Delta(\Theta(t)) = L(\Theta(t+1)) - L(\Theta(t)) \tag{11}$$

$$W = \Delta(\Theta(t)) - VR(t) \tag{12}$$

After calculations, we have the upper bound of W expressed as Eq.(13), where B is the upper bound of $B(t) = \frac{1}{2}\sum_{i=1}^{I}(a_i(t) - u_i(t))^2$.

$$W \le B + \sum_{i=1}^{I} Q_i(t)(a_i(t) - u_i(t)) - VR(t) \tag{13}$$

With the queueing model presented in the previous section, we have

$$\begin{aligned} W &\le B - VR(t) + \sum_{i=1}^{I} Q_i(t)(a_i(t) - u_i(t)) \\ &= B - \frac{V\sum_{i=1}^{I} a_i(t)}{p(t)} + \sum_{i=1}^{I} Q_i(t)(a_i(t) - u_i(t)) \\ &= B - \sum_{i=1}^{I} a_i(t)(\frac{V}{p(t)} - Q_i(t)) - \sum_{i=1}^{I} u_i(t)Q_i(t) \end{aligned} \tag{14}$$

Hence, we transfer the original optimization problem into the upper bound minimization problem as

$$\min_{p(t),a_i(t),u_i(t)} B - \sum_{i=1}^{I} a_i(t)(\frac{V}{p(t)} - Q_i(t)) - \sum_{i=1}^{I} u_i(t)Q_i(t) \tag{15}$$

2. Task scheduling algorithm

In this subsection, we design an algorithm to solve the optimization problem expressed by Eq.(15) practically. We study the formulation and find that B is a constant, and the other two parts of the objective function can be dealt with independently. Although there is correlation between $a_i(t)$ and $p(t)$ both of which are decision variables, we are able to transfer the problem into trying out every possible $p(t)$ in each time slot and solving the following two optimization problems shown by Eqs.(16) and (17) since the power states of sensor hubs are always discrete valued from a few feasible states. Therefore, the objective is to solve the two max-weight problems independently, which can be simultaneously calculated by some well-known linear programming algorithms.

$$\max_{a_i(t)} \sum_{i=1}^{I} a_i(t)\left(\frac{V}{p(t)} - Q_i(t)\right) \tag{16}$$

$$\max_{u_i(t)} \sum_{i=1}^{I} u_i(t) Q_i(t) \tag{17}$$

From all the above formulations and analyses, we present our energy efficient task scheduling algorithm for sensor hubs shown as Algorithm 1.

Algorithm 1 Energy efficient task scheduling algorithm for sensor hubs

1: In each time slot t, observe the current queue state $Q_i(t)$;
2: $\max Obj = -\infty$;
3: **for all** $p(t)$ **do**
4: **for** $i = 1, 2, \cdots, I$ **do**
5: $W_i = \dfrac{V}{p(t)} - Q_i(t)$;
6: Use linear programming to solve the max-weight problem of Eq.(16) and obtain the optimal $a_i(t)$;
7: Use linear programming to solve the max-weight problem of Eq.(17) and obtain the optimal $u_i(t)$;
8: $obj = \sum_{i=1}^{I} a_i(t)(\dfrac{V}{p} - Q_i(t)) + \sum_{i=1}^{I} u_i(t)Q_i(t)$;
9: **if** $obj > \max Obj$ **then**
10: $\max Obj = obj$;
11: $opt\_a_i(t) = a_i(t)$;
12: $opt\_u_i(t) = u_i(t)$;
13: $opt\_p(t) = p(t)$;
14: **end if**
15: **end for**
16: **end for**
17: **for** $i = 1, 2, \cdots, I$ **do**
18: Update queue status using Eq.(5);
19: **end for**
20: $t = t + 1$;
21: Repeat steps 1 to 21.

V. Experimental Results

1. Dataset and experimental settings

In order to validate the efficacy of our approach in real-life environments, we conduct simulation experiments based on an open-source dataset from a real-world Internet of vehicles (IoV) environment. The dataset, namely "T-Drive"[16,17], was released by Microsoft Research. It was collected from a number of GPS loggers and GPS-phones equipped on several taxis in the city of Beijing. In the dataset, there are nearly 15 million pieces of data, consisting of GPS trajectories of 10,357 taxis recorded during a period of one week in the year of 2008. The total distance of the trajectories reached to 9 million kilometers.

For each piece of the data, there is detailed GPS information of a certain taxi including its longitude and latitude, and a timestamp recording the exact time of the data being submitted to the system. We use the GPS data to simulate the workload of a sensor hub, and generate the task arrivals at the time points indicated by its corresponding timestamps.

We conduct experiments using T-Drive dataset for validating the efficacy of the task scheduling approach presented in the previous sections. The tasks are generated according to the information in the T-Drive dataset, our scheduling algorithm is implemented, and experimental data is collected and analyzed. For the basic parameter settings, we suppose that there are 5 buffer queues in each of the sensor hubs with the maximum capacity of 50KB. The time interval between each two decision epoch is set to be 10 seconds, in which each sensor hub should optimize its working status from 5 states including a sleeping mode.

2. Experimental results

In our model, V is a very important parameter which indicates the requirement of users or system managers on the balance of the queue stability and the profit (reward). In our experiments, we tune the parameter V with different values to validate the effectiveness of our approach.

Fig.2 illustrates the experimental results on reward values with different values of parameter V. It is shown that, with the increase of V which means that the reward becomes more important than the queue stability, the reward goes up. However, when V becomes bigger enough (*i.e.*, greater than 30), the effect on the reward brought by the increase of V gets less significant. The reason is that, with a large value of V, the queue status will have less impact on the decision variable $a_i(t)$, making the scheduling algorithm always try to fill up the buffers.

Fig.3 shows the loss rate with the increase of the parameter V. The experimental results indicate that, with the increase of V, the loss rate raises up. When our scheme tries to fill up the buffers when V gets large, it is more possible for the queues to be congested, resulting in a higher loss rate. The results accord with that of Fig.2 and validate the analysis presented above.

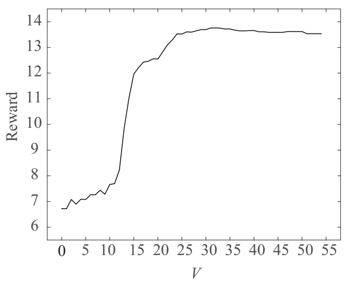

Fig. 2. Rewards with different values of parameter V

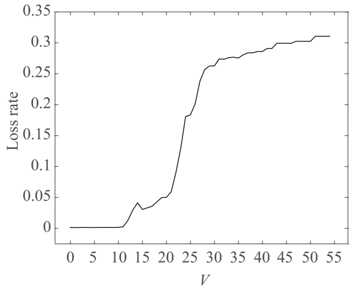

Fig. 3. Loss rates with different values of parameter V

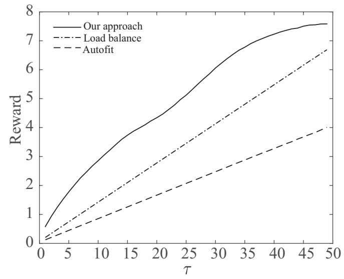

Fig. 4. Comparison among different algorithms

Finally, we compare our approach with some well-known algorithms which have been widely applied in reality. We select two algorithms, first of which namely "Autofit" is to dynamically adjust the power status according to the queue state however ignoring the possibility of queue congestion in the future. The second algorithm for comparison is to fix the CPU or MCU of the sensor hub always working at the full speed resulting in the maximum power consumption. Fig.4 shows the experimental results. It is indicated that our approach is able to achieve the highest reward value. In the experiments, we tune the length of the decision interval. It is obvious that the reward value goes up with the expansion of the decision interval, because of more data being processed in each interval. Also, we can conclude from the experimental data that our algorithm always performs better than the other two algorithms, which validates the effectiveness of our approach.

VI. Conclusions

Energy efficiency is always an important issue in WSN. With the emergence of IoT, the energy consumption in sensor hubs should be increasingly paid attention to. In this paper, we formulate the sensor hubs with queueing theory, and present the optimization model of energy efficient task scheduling. We apply Lyapunov technique for solving the optimization problem, and transfer the original stochastic optimization problem into two subproblems which are much easier to deal with. A multi-queue approach is presented and the scheduling algorithm is designed. Simulation experiments based on real-life data are conducted to validate the efficacy of our approach. This work is expected to provide theoretical and technical reference to the design and optimization of the sensor hubs especially in large-scale IoT environments.

References

[1] J. Gubbi, R. Buyya, S. Marusic, *et al.*, "Internet of things (IoT): A vision, architectural elements, and future directions", *Future Generation Computer Systems*, Vol.29, No.7, pp.1645–1660, 2013.

[2] N. Mohamed, J. Al-Jaroodi, I. Jawhar, *et al.*, "SmartCityWare: A service-oriented middleware for cloud and fog enabled smart city services", *IEEE Access*, Vol.5, pp.17 576–17 588, 2017.

[3] T. Chien, L. Chiou, S. Sheu, *et al.*, "Low-power MCU with embedded ReRAM buffers as sensor hub for IoT applications", *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, Vol.6, No.2, pp.247–257, 2016.

[4] S. Liu, S. Gao and L. Han, "A hybrid approach to maximize lifetime in connected directional sensor networks with adjustable sensing ranges", *Chinese Journal of Electronics*, Vol.27, No.1, pp.159–167, 2018.

[5] Y. Chen, N. Zhang, Y. Zhang, *et al.*, "Energy efficient dynamic offloading in mobile edge computing for Internet of things", *IEEE Transactions on Cloud Computing*, Vol.PP, No.99, pp.1–11, 2019.

[6] M. Hayashikoshi, Y. Sato, H. Ueki, *et al.*, "Normally-off MCU architecture for low-power sensor node", *2014 19th Asia and South Pacific Design Automation Conference* (*ASP-DAC*), pp.12–16, 2014

[7] Y. Song, C. Zhang and Y. Fang, "Minimum energy scheduling in multi-hop wireless networks with retransmissions", *IEEE Transactions on Wireless Communications*, Vol.9, No.1, pp.348–355, 2010.

[8] R. Tang, J. Zhao and H. Qu, "Performance tradeoff between energy conservation and user fairness for D2D communication underlaying cellular networks", *Chinese Journal of Electronics*, Vol.26, No.3, pp.600–607, 2017.

[9] C. Tunca, S. Isik, M. Y. Donmez, *et al.*, "Ring routing: An energy-efficient routing protocol for wireless sensor networks with a mobile sink", *IEEE Transactions on Mobile Computing*, Vol.14, No.9, pp.1947–1960, 2015.

[10] G. Dai, C. Miao, K. Ying, *et al.*, "An energy efficient MAC protocol for linear WSNs", *Chinese Journal of Electronics*, Vol.24, No.4, pp.725–729, 2015.

[11] M. Song and M. Zheng, "Energy efficiency optimization for wireless powered sensor networks with nonorthogonal multiple access", *IEEE Sensors Letters*, Vol.2, No.1, pp.1–4, 2018.

[12] S. Guo, Y. Shi, Y. Yang, *et al.*, "Energy efficiency maximization in mobile wireless energy harvesting sensor networks," *IEEE Transactions on Mobile Computing*, Vol.17, No.7, pp.1524–1537, 2018.

[13] R. R. Rout and S. K. Ghosh, "Enhancement of lifetime using duty cycle and network coding in wireless sensor networks", *IEEE Transactions on Wireless Communications*, Vol.12, No.2, pp.656–667, 2013.

[14] W. Yan, Y. Dong, S. Zhang, *et al.*, "An optimal CDG framework for energy efficient WSNs", *Chinese Journal of*

Electronics, Vol.26, No.1, pp.137–144, 2017.

[15] Y. Chen, N. Zhang, Y. Zhang, *et al.*, "TOFFEE: Task offloading and frequency scaling for energy efficiency of mobile devices in mobile edge computing", *IEEE Transactions on Cloud Computing*, Vol.PP, No.99, pp.1–11, 2019.

[16] J. Yuan, Y. Zheng, C. Zhang, *et al.*, "T-drive: Driving directions based on taxi trajectories", *Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems* (*GIS 2010*), pp.99–108, 2010.

[17] J. Yuan, Y. Zheng, X. Xie, *et al.*, "Driving with knowledge from the physical world", *Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (*KDD 2011*), pp.316–324, 2011.

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