

Towards Energy Optimization Using Joint Data Rate Adaptation for BSN and WiFi Networks

Yantao Li ^{#*1}, Ge Peng ^{*2}, Xin Qi ^{*3}, Gang Zhou ^{*4}, Di Xiao ^{#5}, Shaojiang Deng ^{#6}, Hongyu Huang ^{#7}

*#College of Computer Science, Chongqing University
Chongqing 400044, China*

{¹yantaoli, ⁵dixiao, ⁶sj_deng, ⁷hyhuang}@cqu.edu.cn

**Department of Computer Science, The College of William and Mary
Williamsburg, VA 23187, USA*

{¹yantaoli, ²gpeng, ³xqi, ⁴gzhou}@cs.wm.edu

Abstract—Body sensor networks (BSNs) and WiFi networks have been widely investigated due to the availability of sensor motes and WiFi devices, but they are commonly deployed separately. In this paper we propose to optimize the total communication energy consumption of BSN and WiFi (BSN-WiFi) networks using joint data rate adaptation. More specifically, we first elaborate the BSN-WiFi network system in four consecutive phases. Then based on the system, we analyze the communication energy consumption, throughput and time delay, and provide a signal-to-noise ratio and packet delivery ratio (SNR-PDR) mappings of BSN and WiFi networks. Next, we build an energy optimization model with constraints of SNR-PDR mappings, throughput, and time delay to minimize the total communication energy consumption in BSN-WiFi networks. With the input of SNR values, we solve this model by *cvx* to obtain the output of optimal data rates associated with SNR values, which are then tabulated for online data rate adaptation. Finally, we collect 20-minute traces from a specific BSN-WiFi network system for performance evaluation, and the results demonstrate that our optimal data rate solution achieves up to 86% energy savings comparing with the solutions using fixed data rates.

I. INTRODUCTION

Wireless networks are becoming more and more important for human daily life by providing a wide range of applications, such as reliable fall detection for elderly [1], personal health care monitoring [2], smartphone uploading and downloading, and video game console *Wii*. In all of these applications, the rapid battery depletion of the devices is a common issue. For example, in personal health care system, energy constrained motes collecting and transmitting data rapidly deplete the battery and smartphone connecting to the Internet through WiFi for downloading can not last long. As an energy efficient approach, variable data rate can reduce not only communication energy consumption, but also time delay and congestion. More specifically, data rate adaptation is the process of dynamically switching data rate to match the channel conditions, with the goal of selecting the rate that will provide the optimum throughput for the given channel conditions, thereby optimizing communication energy consumption [3]. Therefore, data rate adaptation pursuing energy efficiency in wireless networks is increasingly attractive.

Wireless sensor networks (WSNs) especially body sensor

networks (BSNs) and WiFi networks are two types of popular wireless networks that have been widely studied and deployed. We build a BSN and WiFi (BSN-WiFi) network system to investigate the approaches that pursue energy efficiency, which is obviously composed of a BSN and a WiFi network. A BSN consists of a collection of small and low power sensing motes, such as EKG, pulse oximeter and temperature, and a resource-rich data aggregation device (aggregator), such as a smartphone connected with a sink mote [4][5]. Normally, motes are attached on human body to sense the physiological readings or activities while the aggregator is used to store or forward the sensed data. BSNs have been deployed in a wide range of applications, such as physical fitness assessment [6], context awareness [7], assisted living [8] and emergency response [9]. On the other hand, a WiFi network is generally composed of an aggregator that is the same in BSN and an access point (AP) connected to the Internet through cables. A common application of WiFi networks is that people use smartphone to browse web sites or send/receive emails [5]. The BSN-WiFi network system can be deployed for many application scenarios such as real-time patient health care and battle field monitoring. For the scenario of the system, data transfer over BSN-WiFi networks starts from the aggregator. With current channel condition, the aggregator first broadcasts a polling message carrying the destination mote ID and an optimal data rate. Then the destination mote responds to the aggregator with a BSN data packet using specified data rate. After receiving a fixed number of BSN data packets, the aggregator combines them into a WiFi data packet and then delivers it with optimal data rate to the AP over WiFi networks.

There are a large number of existing works investigating data rate adaptation in WSNs or WiFi networks, but not both. For WSNs, the authors in [10] present an addition to the 802.15.4 specification adding *500kbps*, *1000kbps* and *2000kbps* data rates to the existing *250kbps* with a minimum of hardware changes. This approach provides us variable data rates in BSN. Some data rate adaptation algorithms are proposed to pursue energy efficiency [11][12]. Other approaches [13][14] propose link adaptation strategies that increase data

rates if SNR is large. For WiFi networks, some statistics based algorithms [15][16][17] attempt to reduce probing overhead by choosing adaptive success/failure threshold for rate increase/decrease. Other statistics based algorithms are provided [18][19][20]. Some PHY-metric based algorithms are proposed as well [3][21][22][23][24]. There are some works considering the coexistence of BSN-WiFi networks [25][26][27], but not for energy efficiency. The authors of [28] propose an energy optimization solution for BSN-WiFi networks through adjustable packet sizes, but we adopt data rate adaptation to optimize energy consumption.

Different from the aforementioned works, we attempt to optimize the total communication energy consumption in BSN-WiFi networks. Data rate adaptation is an effective approach for energy efficiency [3][20][22][29], and we use SNR that directly characterizes the channel quality to assist the data rate adaptation. If SNR value increases, a higher data rate is adopted; if SNR value reduces, a lower data rate is needed. Therefore, we are able to optimize the energy consumption of BSN-WiFi networks by joint data rate adaptation.

In this paper, we aim to use joint data rate adaptation to optimize the total communication energy consumption in BSN-WiFi networks. More specifically, we first illustrate a BSN-WiFi network system that is composed of a BSN and a WiFi network and then we divide the system communication into four consecutive phases to explain how the data is transmitted from motes to the AP. Next, we analyze the energy consumption, throughput, time delay, and SNR-PDR mappings in both the BSN and the WiFi networks, respectively. Based on the analysis, we build an energy optimization model with constraints of SNR-PDR mappings, throughput and time delay, which is further demonstrated to be a GP problem. With the input of SNR values, we solve this model by *cvx* and obtain the output of optimal data rates associated with SNR values. Then, we tabulate SNR values and associated data rate values for online data rate adaptation according to the current channel condition. For performance evaluation, we collect 20-minute traces from a specific BSN-WiFi network system. We demonstrate that our optimal data rate solution can save up to 86% energy, comparing with the solutions that use fixed data rates.

The main contributions of this work can be summarized as:

- We present the joint data rate adaptation approach to optimize the total communication energy consumption in BSN-WiFi networks.
- We analyze the communication energy consumption, throughput, time delay, and SNR-PDR mappings of BSN and WiFi networks, respectively, and then build an energy optimization model with constraints of SNR-PDR mappings, throughput, and time delay. We solve this model by *cvx* and then tabulate the results for online usage.
- We collect 20-minute traces for performance evaluation and our results demonstrate that the optimal data rate solution can achieve up to 86% energy savings comparing with the solutions using fixed data rates.

The rest of this paper is organized as follows: Section II

presents related work. Section III describes the BSN-WiFi network system in detail and based on the system, Section IV provides the total communication energy consumption, analyzes the throughput and time delay, and presents SNR-PDR mappings. Then, we build an energy optimization model with constraints of SNR-PDR mappings, throughput and time delay for the BSN-WiFi network system in Section V. In Section VI, we evaluate the energy optimization solution and present conclusions in Section VII.

II. RELATED WORK

A large number of methods performing rate adaptation in WSNs or WiFi networks have been studied. In the following, we broadly categorize these approaches into rate adaptation in WSNs, in WiFi networks, and coexistence of BSN-WiFi networks.

A. Rate Adaptation in WSNs

Rate adaptation methods in WSNs can be classified into energy-efficiency based algorithms, and PHY-metric based algorithms, where the data rate is selected in accordance with PHY layer metrics, such as SNR, SINR, RSSI, etc.

Energy-efficiency based algorithm. The authors of [10] propose DRACER (Dynamic Rate Adaptation and Control for Energy Reduction), which is an addition to the IEEE 802.15.4 specification along with a media access layer extension to select the appropriate data rate. In [11], the authors present an adaptive-CSMA/CA protocol, which accounts for varying channel and load conditions at a node by influencing the selection of either low energy or low delay transmission option. The work of [12] addresses the throughput optimization problem for a rate-adaptive energy harvesting node that chooses its rate from a set of discrete rates and adjusts its power depending on its channel gain and battery state.

PHY-metric based algorithm. In [13], the authors propose a novel LA (Link Adaptation) strategy, where nodes select the modulation scheme according to the experienced channel quality and level of interference. For example, if both the SNR is large and the signal-to-interference ratio (SINR) is low, nodes increase the bit rate, in order to decrease the time that the channel is occupied and the collision probability. Based on [13], the authors propose to use the LA in wireless body area network scenario, with the aim of reducing packet losses in [14], where nodes increase the bit rate, if the SNR is large, regardless of the actual interference.

However, the aforementioned works only focus on rate adaptation in wireless sensor networks but not in heterogeneous networks, such as BSN-WiFi networks.

B. Rate Adaptation in WiFi networks

Rate adaptation approaches in WiFi networks can be categorized into statistics based algorithms, where the data rate is adapted according to the packet retransmission history, and PHY-metric based algorithms.

Statistics based algorithm. In [15], the authors are among the first to present ARF (Automatic Rate Fallback) addressing

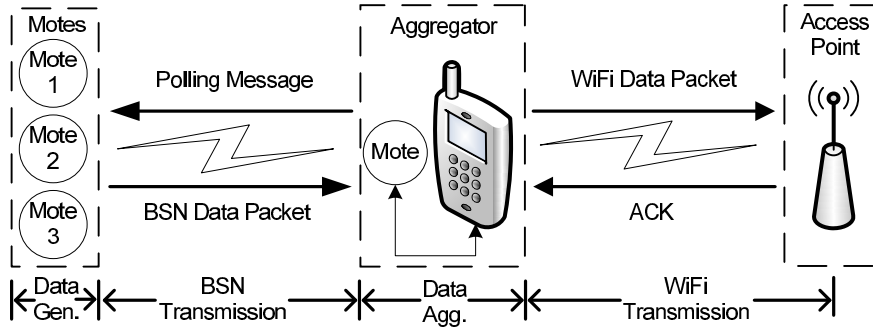


Fig. 1: The BSN-WiFi network system

rate adaptation, where the data rate is increased after ten consecutive packets are successfully delivered and decreased when suffering two successive transmission failures. Then, two extensions are provided: AARF (Adaptive ARF) scheme [16], which provides both short-term and long-term adaptation, and FRLA (Fast-Responsive Link Adaptation) scheme [17], which adjusts the probing interval dynamically to the wireless channel variation. In [18], the authors present the SampleRate bit rate selection algorithm, that switches current bit rate to a different bit rate if the throughput estimate based on recorded loss rate with the other bit rate is higher than the throughput with the current bit rate. The authors of [19] propose CARA (Collision-Aware Rate Adaptation) scheme, where the transmitter station adaptively combines the RTS/CTS exchange with the clear channel assessment (CCA) functionality to differentiate frame collisions from frame transmission failures caused by channel errors. In [20], the authors present RAF (Rate-Adaptive Framing) that jointly controls the channel rate and frame size according to the observed interference patterns and noise level at the receiver.

PHY-metric based algorithm. The authors of [3] propose RBAR (Receiver-Based AutoRate), which adopts RTS/CTS to obtain SNR and then selects data rates through a predefined SNR data rate lookup table. In [21], the authors develop CHARM (CHannel-Aware Rate adaptation algorithm), which uses signal strength measurements collected by the wireless cards to help select the transmission rate. The authors in [22] present a practical SGRA (SNR-Guided Rate Adaptation) scheme: if the channel is in interference-free state, it aggressively exploits the SNR value to predict the optimal rate; if the channel is interfered, it uses SNR as a guideline to select a set of candidate rates, but relies on probing to obtain the optimal selection. In [23], the authors present SoftRate, a wireless bit rate adaptation protocol that uses confidence information to estimate the prevailing channel bit error rate (BER). The confidence information is calculated by the physical layer and then is exported to higher layers via the SoftPHY interface. The authors of [24] adopt an online measurement of FPR(Frame Delivery Ratio)-RSSI mapping to choose bit rate based on the joint consideration of RSSI and transmission power.

Nevertheless, these approaches mainly emphasize rate adap-

tation in WiFi networks with the aim of maximizing throughput, while we lie on it in both BSN and WiFi networks with the goal of optimizing the total communication energy consumption.

C. Coexistence in BSN-WiFi networks

There are some works on coexistence of BSN-WiFi networks: the authors of [25] provide a coexistence scheme of BSN and WiFi networks by using multiple radio channels, and in [26] authors present a WISE protocol that enables ZigBee links to achieve assured performance in the presence of heavy WiFi interference. In [27], the authors design BuzzBuzz to mitigate WiFi interference through header and payload redundancy in low power ZigBee networks. However, they only focus on the interference between BSN and WiFi networks, ignoring energy efficiency. The authors of [28] propose an energy optimization solution for BSN-WiFi networks through adjustable packet sizes, but we are different in optimizing energy consumption using joint data rate adaptation.

III. BSN-WiFi NETWORK SYSTEM

In this section, we illustrate the BSN-WiFi network system with data flow diagram as shown in Figure 1. As depicted in Figure 1, the BSN-WiFi network system consists of a BSN, which is composed of a group of motes and an aggregator, and a WiFi network, which is constituted of the aggregator, an AP, and possibly other clients not shown here. In particular, we use a smartphone connected with a sink mote via USB as an aggregator [30]. On the aggregator, the sink mote is used to communicate with all the motes and then it transfers data to the smartphone, while the smartphone is used for transmitting data to the AP. In order to fully analyze the BSN-WiFi network system, we divide the data flow into four consecutive phases: Data Generation, BSN Transmission, Data Aggregation, and WiFi Transmission.

A. Data Generation

In this phase, all the motes generate data to transmit. For mote n ($n \in \{1, 2, \dots, N\}$), we use b_n to denote its data generation rate. Then, the data generation rate of all the motes is $\sum_{n=1}^N b_n$ and the average data generation rate is $\sum_{n=1}^N b_n / N$. Therefore, the expected time required for one mote to generate one bit data is $N / \sum_{n=1}^N b_n$.

B. BSN Transmission

In the BSN, all the motes attempt to transmit the generated data to the aggregator. It begins with the aggregator broadcasting a polling message to all the motes and then the assigned mote responds with a BSN data packet to the aggregator. The polling message is used to notify all the motes about what mote is selected to transmit BSN packets and what data rate is required according to the current SNR. We use l_m to denote the length of a BSN data packet, h_m to indicate header length for both polling message and BSN data packet, and r_m to represent the data rate in BSN. Furthermore, we use l_p to indicate the length of a polling message, which is composed of header with length of h_m , 1 byte mote ID information and 2 bytes data rate information. Thus, the time required by the aggregator to broadcast a polling message to all the motes is l_p/r_m and the time needed by the mote to send back a BSN data packet to the aggregator is l_m/r_m . In addition, we use p_{r_m} to denote the PDR of data transmission between all the motes and the aggregator in both directions when using data rate r_m . As we designed, packets transmission between motes and the aggregator is one polling message for one BSN data packet. For this reason, the transmission failure of either a polling message itself or the corresponding BSN data packet will trigger the retransmission of the polling message, while the failed delivery of a BSN data packet will only cause the retransmission of the same BSN data packet. Hence, the expected retransmission number of a successful delivery of a polling message is $1/p_{r_m}^2$ and the expected retransmission number for a successful delivery of the corresponding BSN data packet is $1/p_{r_m}$. Therefore, the expected time delay of a successful transmission of a BSN data packet from the assigned mote to an aggregator is $\frac{l_p}{r_m} \times \frac{1}{p_{r_m}^2} + \frac{l_m}{r_m} \times \frac{1}{p_{r_m}}$.

C. Data Aggregation

In this phase, the aggregator needs to wait for multiple BSN data packets coming from motes, removes the headers of these packets that received, and then aggregates these payloads into a WiFi data packet with a new header. Assuming that we use l_a and h_a to denote the total length and header length of a WiFi data packet, a WiFi data packet is composed of the total payloads of $\frac{l_a-h_a}{l_m-h_m}$ BSN data packets. Since the transmission in BSN and the data aggregation in WiFi network are in parallel, the actual delay in aggregation is the waiting time for the remaining $\frac{l_a-h_a}{l_m-h_m} - 1$ BSN data packets after the arrival of the earliest BSN data packet. Therefore, the time delay in data aggregation phase is $\frac{l_m-h_m}{\sum_{n=1}^N b_n} \times (\frac{l_a-h_a}{l_m-h_m} - 1)$.

D. WiFi Transmission

In the WiFi network, the aggregator transmits the aggregated WiFi data packets to the AP following IEEE 802.11 standard [31]. The WiFi transmission starts with the aggregator carrier sensing the channel condition and then it sends out a WiFi data packet to the AP when the channel is clear. After receiving the packet, the AP replies an ACK to the aggregator when the channel is clear.

First of all, we briefly introduce the CSMA protocol used in current WiFi devices. According to the default setting in commercial WiFi devices, we turn off the RTS-CTS exchange in CSMA protocol. In this CSMA protocol, the aggregator first carrier senses the wireless channel condition. If the channel is idle, it sends out the WiFi data packet immediately. Otherwise, it randomly selects a time interval within $[0, cw]$ as a backoff time counter before transmission, where cw denotes the backoff time. The backoff time counter decrements as long as the channel is sensed idle, stops when a transmission is detected on the channel, and reactivates when the channel is sensed idle again. The aggregator transmits WiFi data packets when the backoff counter reaches zero and the channel is clear. Otherwise, it backs off again. Therefore, the expected backoff time period for a packet transmission is $t_{cw} = cw/2 \times \min\{M - 1/2, R\}$ [32], where $M-1$ is the number of potential contenders sharing the same AP with the aggregator and R is the maximum number of backoff retries.

Then, with r_a representing the data rate in WiFi network, the time required by the aggregator to transmit a WiFi data packet to the AP when the channel is clear is l_a/r_a . Since the ACK message is tiny compared with the WiFi data packet, we assume that there is no ACK failure. If we use p_{r_a} to denote the PDR of data transmission from the aggregator to the AP when using data rate r_a , the expected retransmission number of a successful delivery of a WiFi data packet is $1/p_{r_a}$. Therefore, the expected time delay of a successful transmission of a WiFi data packet from the aggregator to the AP is $(t_{cw} + \frac{l_a}{r_a} \times \frac{1}{p_{r_a}})$.

IV. SYSTEM MODELING

In this section, based on BSN-WiFi network system, we first present the communication energy consumption in detail, then analyze the constraints of throughput and time delay, and finally propose the SNR-PDR mappings.

A. Energy Consumption

Energy efficiency is a critical issue in energy constrained wireless devices. Communication consumes major battery energy in wireless communications, therefore, in this paper, we only focus on communication energy consumption in BSN and WiFi networks. In this section, we formulate the communication energy consumption problems of BSN and WiFi networks, respectively.

1) *BSN Energy Consumption*: In the BSN, energy is consumed by motes to transmit BSN data packets and receive polling messages, and by the aggregator to broadcast polling messages and receive BSN data packets. With E_{BSN} denoting the total energy consumed by all the motes and the aggregator over any time period t , we get:

$$E_{BSN} = e_{11} + e_{12} \quad (1)$$

where e_{11} represents the energy consumed by motes and e_{12} indicates the energy consumption of the aggregator.

The total energy consumed by N motes to receive polling messages from the aggregator and to transmit BSN data

packets to the aggregator, including retransmissions of polling messages and packets, over any time period t is formulated as:

$$e_{11} = (N \times \frac{l_p}{r_m} \times \frac{1}{p_{r_m}^2} \times P_{mr} + \frac{l_m}{r_m} \times \frac{1}{p_{r_m}} \times P_{mt}) \times \frac{\sum_{n=1}^N b_n \times t}{l_m - h_m} \quad (2)$$

where P_{mr} and P_{mt} represent the power needed by the mote to receive polling messages and to transmit BSN data packets, respectively. Furthermore, $\frac{l_p}{r_m} \times \frac{1}{p_{r_m}^2}$ indicates the expected time needed for one mote to successfully receive a polling message, while $\frac{l_m}{r_m} \times \frac{1}{p_{r_m}}$ represents the expected time required by one mote to successfully transmit a BSN data packet. As we mentioned, a successful delivery of a packet from the mote to the aggregator consists of the successful delivery of both polling message and the corresponding packet. Hence, the sum of energy consumption of both reception and transmission in the parentheses is the energy consumption of successful delivery of a BSN data packet. In addition, with the definition that $l_m - h_m$ denotes the payload length of a BSN data packet, $\frac{\sum_{n=1}^N b_n \times t}{l_m - h_m}$ means how many packets are generated by the N motes over time t , or how many packets should be transmitted.

On the other hand, the total energy consumed by the aggregator to broadcast polling messages to all the motes and receive BSN data packets from the assigned mote, including the retransmission, over any time t , is calculated as:

$$e_{12} = (\frac{l_p}{r_m} \times \frac{1}{p_{r_m}^2} \times P_{mt} + \frac{l_m}{r_m} \times \frac{1}{p_{r_m}} \times P_{mr}) \times \frac{\sum_{n=1}^N b_n \times t}{l_m - h_m} \quad (3)$$

where P_{mt} and P_{mr} indicate the power of the sink mote on the aggregator to broadcast polling messages and to receive BSN data packets, respectively. Here, we use the sink mote to broadcast and receive instead of the smartphone, since motes are unable to directly communicate with the smartphone. For this reason, we connect a sink mote with a smartphone via USB [30] as the aggregator.

2) *WiFi Energy Consumption:* According to IEEE 802.11, after the AP receives a WiFi data packet, it will reply an ACK to the aggregator. Since the ACK is tiny compared with a WiFi data packet, we assume that the aggregator does not consume energy to receive it. Therefore, in the WiFi network, energy is spent by the aggregator carrier sensing the channel condition and then transmitting WiFi data packets to the AP. With retransmission, the payload in BSN data packets finally received by the aggregator should be $\sum_{n=1}^N b_n \times t$, which is then delivered to the AP in the form of WiFi data packets. Assuming that we use E_{WiFi} to represent the total energy consumption of the aggregator to transmit WiFi data packets to the AP, we obtain:

$$E_{WiFi} = e_{21} + e_{22} \quad (4)$$

where e_{21} and e_{22} denote the energy consumption for carrier sensing and for transmitting WiFi data packets, respectively.

At the beginning of every packet transmission, the aggregator carrier senses the channel condition for an expected

time period t_{cw} . Thus, the energy spent for carrier sensing, including the situation of WiFi packet transmission failure, over any time period t , is expressed as:

$$e_{21} = t_{cw} \times \frac{1}{p_{r_a}} \times P_{as} \times \frac{\sum_{n=1}^N b_n \times t}{l_a - h_a} \quad (5)$$

where P_{as} denotes the power of the aggregator for carrier sensing. Furthermore, $t_{cw} \times \frac{1}{p_{r_a}}$ means the expected carrier sensing time for a successful transmission of a WiFi data packet and $l_a - h_a$ is the payload length of a WiFi data packet.

When the transmission channel is clear, the aggregator transmits a WiFi data packet immediately. Thus, the energy spent by the aggregator, including retransmission, over any time period t , is calculated as:

$$e_{22} = \frac{l_a}{r_a} \times \frac{1}{p_{r_a}} \times P_{at} \times \frac{\sum_{n=1}^N b_n \times t}{l_a - h_a} \quad (6)$$

where P_{at} denotes the power of the aggregator to transmit WiFi data packets. In addition, $\frac{l_a}{r_a} \times \frac{1}{p_{r_a}}$ is the expected time for a successful delivery of a WiFi data packet.

B. Throughput Constraint

Since we use data rate adaptation in BSN-WiFi network communication, we need to make sure that the data throughput is less than or equal to the optimal data rate [33]. We analyze the throughput of BSN (θ_{BSN}) and WiFi network (θ_{WiFi}), respectively, in the following:

1) *BSN Throughput Constraint:* Within a unit time period (e.g., 1 second), data is transmitted as polling messages and BSN data packets in the BSN, hence, the throughput constraint of BSN is expressed as:

$$l_p \times \frac{\sum_{n=1}^N b_n}{l_m - h_m} \times \frac{1}{p_{r_m}^2} + \sum_{n=1}^N b_n \times \frac{l_m}{l_m - h_m} \times \frac{1}{p_{r_m}} \leq r_m \quad (7)$$

where $\frac{\sum_{n=1}^N b_n}{l_m - h_m}$ denotes the number of polling messages transmitted from the aggregator, and $l_p \times \frac{\sum_{n=1}^N b_n}{l_m - h_m}$ means the total amount of data in polling messages, and $\sum_{n=1}^N b_n \times \frac{l_m}{l_m - h_m}$ represents the total amount of data in BSN data packets, including the header data of each packet. Taking the retransmission of polling message and BSN data packets into account, the total amount of data transmitted per unit time should be less than or equal to the current data rate r_m , namely, $\theta_{BSN} \leq r_m$.

2) *WiFi Throughput Constraint:* Within a unit time period (e.g., 1 second), data is delivered as WiFi data packets in the WiFi networks, therefore, the throughput constraint of WiFi network is formulated as:

$$\sum_{n=1}^N b_n \times \frac{l_a}{l_a - h_a} \times \frac{1}{p_{r_a}} \leq r_a \quad (8)$$

where $\sum_{n=1}^N b_n \times \frac{l_a}{l_a - h_a}$ denotes the amount of data in WiFi data packet. Considering retransmissions of WiFi data packets, the total amount data delivered per unit time should be less than or equal to the current data rate r_a , namely, $\theta_{WiFi} \leq r_a$.

C. Time Delay Constraint

For real time applications, the time delay is a rigorous requirement, such as Voice over IP (VoIP). Thus, the time delay requirement of BSN-WiFi networks is formulated as:

$$\frac{l_m - h_m}{\sum_{n=1}^N b_n / N} + \frac{l_p}{r_m} \times \frac{1}{p_{r_m}^2} + \frac{l_m}{r_m} \times \frac{1}{p_{r_m}} + \frac{l_m - h_m}{\sum_{n=1}^N b_n} \times \left(\frac{l_a - h_a}{l_m - h_m} - 1 \right) + (t_{cw} + \frac{l_a}{r_a}) \times \frac{1}{p_{r_a}} \leq D \quad (9)$$

where D denotes the required time delay by real time application. With the analysis in Section III, we explain the total time delay in BSN-WiFi networks ($\tau_{BSN-WiFi}$) as a pipelined data flow: (i) First, all the motes spend time on generating packets, hence, the average time delay for generating a BSN data packet is $\frac{l_m - h_m}{\sum_{n=1}^N b_n / N}$. (ii) Then, the BSN data packet is transmitted to the aggregator with the time delay $\frac{l_p}{r_m} \times \frac{1}{p_{r_m}^2} + \frac{l_m}{r_m} \times \frac{1}{p_{r_m}}$ under data rate r_m . (iii) Next, the aggregator waits for $\frac{l_a - h_a}{l_m - h_m} - 1$ BSN data packets coming from motes and then composes a WiFi data packet with the received BSN data packet, which takes the time of $\frac{l_m - h_m}{\sum_{n=1}^N b_n} \times (\frac{l_a - h_a}{l_m - h_m} - 1)$. (iv) Finally, the aggregator transmits the WiFi data packet to the AP with time $(t_{cw} + \frac{l_a}{r_a}) \times \frac{1}{p_{r_a}}$.

D. SNR-PDR Mappings

An unsolved problem in above subsections is how to obtain p_{r_m} and p_{r_a} , which are the PDRs under the data rates r_m and r_a , in BSN and WiFi networks, respectively. It is known that exploiting PHY layer information that directly characterizes the channel quality will give a better guideline for data rate adaptation, since many schemes have been proposed to use SNR to assist the data rate adaptation, such as RBAR (Receiver-Based AutoRate) [3], RAF (Rate-Adaptive Framing) [20], SGRA (SNR-Guided Rate Adaptation) [22] and OAR (Opportunistic Auto Rate) [29]. In addition, SNR is an efficient metric for estimating the optimal data rate as well. Therefore, to address the problem, we are challenged to find the map of one SNR for one optimal data rate through building BSN SNR-PDR model in Section IV-D.1 and WiFi SNR-PDR model in Section IV-D.2.

1) *BSN SNR-PDR mapping*: As mentioned in [10], they add 500kbps, 1000kbps and 2000kbps data rates to the existing data rate 250kbps in IEEE 802.15.4 specification [34] with a minimum of hardware changes. That makes variable data rate adaptation feasible for this work. Therefore, we define that the data rate r_m in BSN is valued in the set $r_{BSN} : \{250kbps, 500kbps, 1000kbps, 2000kbps\}$, namely, $r_m \in r_{BSN}$. Based on the analysis in [10], we obtain the map of SNR to PDR under the data rate r_m in BSN:

$$p_{r_m} = \left(1 - \frac{2^k - 1}{2} \times \exp \left(-\sqrt{\left(u \times \frac{S_{r_m}}{2} \right)} \right) \right)^v \quad (10)$$

where S_{r_m} denotes the current SNR under the data rate r_m and p_{r_m} represents the current PDR under the data rate r_m .

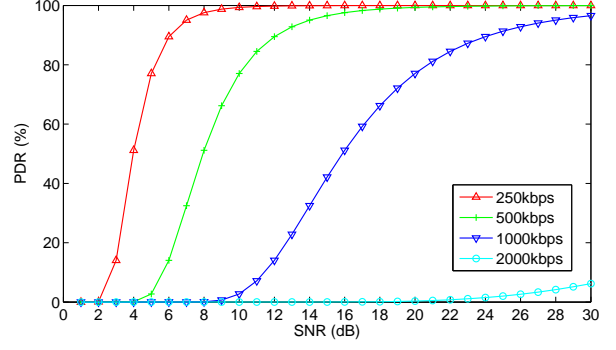


Fig. 2: SNR-PDR mapping of BSN

The exponent v is the length of BSN data packet in symbols. k and u are parameters in coding scheme, which means that k bits are encoded together into a u chip signal. For easy denotation, we define SNR-PDR model in BSN as $p_{r_m} = f(S_{r_m})$. Since we do not focus on the coding scheme, we just list the parameters used in Equation 10 under different data rates in Table I.

TABLE I: Parameters for SNR-PDR Model in BSN

$k(bit)$	$u(chip)$	$r_m(kbps)$
4	32	250
4	16	500
4	8	1000
1	1	2000

The values of SNR in BSN normally range in [1dB, 30dB] [10][35], therefore, based on Equation 10 and Table I, we plot Figure 2 to show the correlation between SNR and PDR under r_{BSN} . As illustrated in Figure 2, the PDRs of all the data rates rise when SNR increases, hence, we can deduce that $p_{r_m} = f(S_{r_m})$ is a monotonic increasing function. Then, a further observation is that a lower data rate grows faster than a higher one as SNR increases. The reason is that when the link quality is poor, namely, low PDR or small SNR, lower data rate is preferred, while when it is good, higher data rate has priority. In addition, we can also see that for a specific SNR value, there are $|r_{BSN}| = 4$ PDR values associated with $|r_{BSN}| = 4$ data rates.

2) *WiFi SNR-PDR mapping*: Since IEEE 802.11 standard [31] has defined multiple data rates, the available values of data rate r_a in WiFi networks lie in the set $r_{WiFi} : \{6Mbps, 12Mbps, 18Mbps, 24Mbps, 35Mbps, 48Mbps, 54Mbps\}$ [22][36], namely, $r_a \in r_{WiFi}$. The values of SNR in WiFi networks usually lie in [1dB, 40dB] and according to the data values in Figure 5 of [36], we replot a color Figure 3 to demonstrate the correlation between SNR and PDR under r_{WiFi} . We define the PDR-SNR mapping of WiFi networks as a function of $p_{r_a} = f(S_{r_a})$. As depicted in Figure 3, obviously, the PDRs for all the data rates increase as SNR grows. Thus, $p_{r_a} = f(S_{r_a})$ is a monotonic increasing function as well. A further observation is that with the increase of SNR, the PDR values of lower data rates grow faster than that of

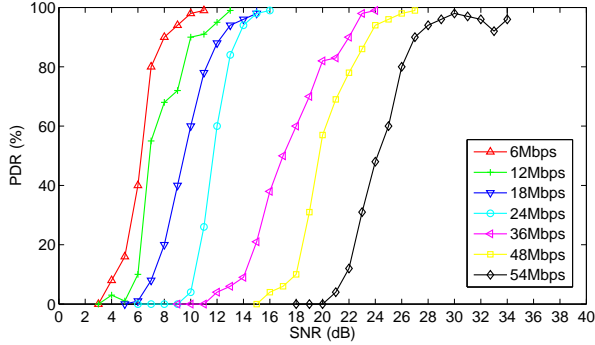


Fig. 3: SNR-PDR mapping of WiFi networks

higher ones. Moreover, there are $|r_{WiFi}| = 7$ PDR values associated with $|r_{WiFi}| = 7$ data rates for each SNR value as well.

3) *SNR measurements*: For SNR measurement in BSN, we refer to the measurement method in [35]: since each mote is equipped with an IEEE 802.15.4 compliant Chipcon CC2420 radio, the received signal strength indicator (RSSI) of CC2420 at the aggregator contains the measurement of signal power P_{sm} in dBm and if there are no incoming packets, the RSSI value is the signal power of environmental noise P_{nm} in dBm . Therefore, the SNR in BSN can be computed as: $S_{BSN} = \frac{P_{sm} - P_{nm}}{P_{nm}}$.

On the other hand, for SNR measurement in WiFi networks, we refer to the approach provided in [37]: RSSI values reported by network interface cards (NICs) give an estimate of the signal power denoted as P_{sa} in dBm for each received packets and the signal power of environmental noise expressed as P_{na} in dBm if there are no incoming packets. Thus, the SNR in WiFi networks can be calculated as: $S_{WiFi} = \frac{P_{sa} - P_{na}}{P_{na}}$.

Before entering into Section V, we discuss the combinations of SNRs as well as data rates in BSN and WiFi network, respectively. Since S_{r_m} lies in the range [1dB, 30dB] and S_{r_a} falls in [1dB, 40dB], there are 30×40 combinations of (S_{r_m}, S_{r_a}) . On the other hand, as defined, r_m falls in the set r_{BSN} with 4 elements while r_a lies in the set r_{WiFi} with 7 elements. Therefore, for each combination of (S_{r_m}, S_{r_a}) , there are 4×7 combinations of (r_m, r_a) associated with it. Next, we attempt to obtain one out of 28 combinations of (r_m, r_a) for each SNR combination (S_{r_m}, S_{r_a}) through building a communication energy optimization model with constraints of SNR-PDR mappings, throughput, and time delay.

V. ENERGY OPTIMIZATION

Energy efficiency is a critical issue in energy-constrained BSN and WiFi networks. As described in IV-A, the major energy consumption in BSN and WiFi network is on data communication. In this section, we aim to optimize the total communication energy in BSN-WiFi networks using joint data rate adaptation. In the model, we aim to input the SNR values (S_{r_m}, S_{r_a}) and output the corresponding optimal data

rates (r_m, r_a) . More specifically, we first build the energy optimization model for BSN-WiFi networks with constraints of SNR-PDR mappings, throughput, and time delay. Then, we solve this model with *cvx* and tabulate the offline solution for online usage.

A. Energy Optimization modeling

In this section, we build the energy optimization model with constraints of SNR-PDR mappings, throughput, and time delay for BSN-WiFi networks. With the input of SNR values and the output of optimal data rates through solving the model, we attempt to obtain a map between SNR values (S_{r_m}, S_{r_a}) and optimal data rates (r_m, r_a) , meanwhile minimizing the total energy consumption.

$$\text{Minimize } E = E_{BSN} + E_{WiFi} \quad (11)$$

Subject to

$$p_{r_m} = f(S_{r_m}) \quad (12)$$

$$p_{r_a} = f(S_{r_a}) \quad (13)$$

$$\theta_{BSN} \leq r_m \quad (14)$$

$$\theta_{WiFi} \leq r_a \quad (15)$$

$$\tau_{BSN-WiFi} \leq D \quad (16)$$

$$r_m \in r_{BSN}, r_a \in r_{WiFi} \quad (17)$$

where Equation 11 is the objective function, and Equations 12-17 are constraint functions. θ_{BSN} in Equation 14 and θ_{WiFi} in Equation 15 denote the throughput of BSN and WiFi network, respectively. $\tau_{BSN-WiFi}$ in Equation 16 represents the total time delay of BSN-WiFi networks and D is the maximum allowable time delay between the point at which data is generated on motes and the point when data is successfully delivered to the AP required by the applications.

For objective function (Equation 11), with the goal of minimizing the total energy consumption, the input is one SNR combination (S_{r_m}, S_{r_a}) associated with 28 combinations of (r_m, r_a) and the output is the optimal data rates (r_m, r_a) exactly associated with the (S_{r_m}, S_{r_a}) .

For constraint functions, Equation 12 is the map between SNR S_{r_m} associated with data rate r_m and PDRs p_{r_m} in BSN, while Equation 13 is the map between SNR S_{r_a} associated with data rate r_a and PDRs p_{r_a} in WiFi networks. Then, Inequalities 14 and 15 are the constraints of throughput in BSN and WiFi networks, respectively. Next, Inequality 16 is the time delay required by the application, where $\tau_{BSN-WiFi}$ denotes the total time period from when data is generated to when a WiFi data packet is delivered to the AP. Finally, Inequality 17 indicates that the data rates r_m and r_a are discrete values in the sets of r_{BSN} and r_{WiFi} , respectively.

B. Offline Solution and Online Usage

In this section, we first setup the parameters used in the energy optimization model, then solve it by *cvx*, and finally tabulate the offline solution for online dynamical data rate adaptation.

Based on BSN-WiFi network system, suppose that we use three TelosB motes with MSP430F1611 micro controller and

CC2420 ratio as the motes [38], utilize a Sprint HTC Hero smartphone with Android 3.1 connected with a sink mote via USB as an aggregator, and employ a router connected to the Internet through cables as an AP. The parameters in the system for optimizing energy consumption are presented in Table II. Note that the parameters in the table are just a specific setup for the energy optimization model, however, the model is not confined to these parameters.

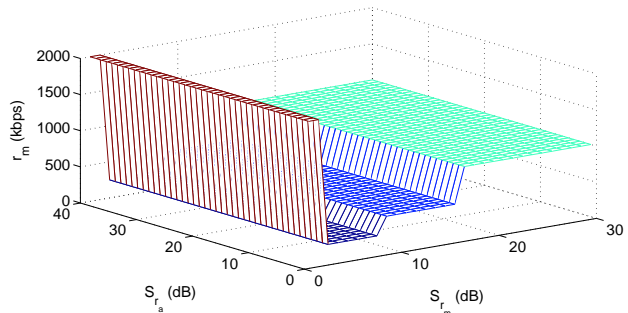
TABLE II: Parameter setup

N	3	P_{mt}	35mW
M	5	P_{mr}	38mW
R	5	P_{at}	1.65W
t	1s	P_{as}	1.15W
l_p	23B	cw	640 μ s
l_m	133B	D	177ms
l_a	272B	b_1	4kbps
h_m	20B	b_2	5kbps
h_a	46B	b_3	5kbps

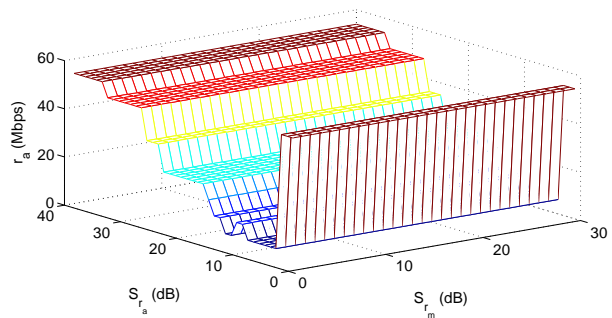
From the table, l_p consists of h_m bytes header, 1 byte mote ID information, and 2 bytes data rate information. We set the WiFi data packet payload length as $l_a - h_a = 226$ bytes, which is in multiple of the BSN data packet payload length $l_m - h_m = 133$ bytes. We assign the time delay $D = 177ms$, according to the requirement of VoIP.

Next, we solve the energy optimization model with the above parameters. Referring to [39], if the model with standard form of Geometric Programming (GP) problem satisfies the two conditions: the coefficients of the functions are any positive numbers and the exponents are any real numbers, then it is a GP problem. Obviously, the energy optimization satisfies the two conditions and is a GP problem. An efficient solution for a GP problem is *cvx* [40], which can be implemented in Matlab. By solving this energy optimization model, we can obtain the offline solutions of optimal data rate r_m for motes in the BSN and r_a for the aggregator in the WiFi networks for all the combinations of (S_{r_m}, S_{r_a}) . For the convenience of analysis, we plot Figure 4 to illustrate the optimal data rates of r_m and r_a with all the SNR combinations of (S_{r_m}, S_{r_a}) . Obviously, the data rates increase as both SNRs increase. More specifically, as depicted in Figure 4(a), the optimal data rate r_m in the BSN increases when SNR S_{r_m} increases. The reason is that when SNR S_{r_m} increases, which means the PDR p_{r_m} is increasing as well, a higher data rate is adapted, which needs less power. However, one exception is that when S_{r_m} is extremely low, the data rate is the highest one 2000kbps. This is because the mote tries its best to transmit the data out in the extreme communication condition. On the other hand, as illustrated in Figure 4(b), the optimal data rate r_a in the WiFi networks increases when SNR S_{r_a} rises. Also, when S_{r_a} is extremely low, the data rate is the highest one 64Mbps.

Therefore, based on results in Figure 4, we can tabulate the offline optimal solutions with 4 columns and 30×40 rows. The columns consist of S_{r_m} , S_{r_a} , r_m , and r_a while the rows are corresponding to the combinations of S_{r_m} and S_{r_a} . Then, the



(a) Optimal Data Rate r_m



(b) Optimal Data Rate r_a

Fig. 4: The Optimal Data Rate Solution

offline optimal solution table can be loaded on the aggregator for online data rate adaptation. Specifically, the aggregator assigns the data rate for the motes in the BSN through polling messages and specifies the data rate for itself in the WiFi network, according to the current received SNR value.

VI. PERFORMANCE EVALUATION

In this section, we first introduce the evaluation setup for collecting traces. Then we evaluate the energy consumption solution in BSN-WiFi networks and compare our optimal data rate solution with solutions that use fixed data rates.

A. Evaluation Setup

A BSN-WiFi network system is presented to mimic a typical assisted living facility, where the BSN is used for monitoring physiological readings of a patient at home and transmitting these generated data to a wireless device (such as a smartphone), the WiFi network is used for transmitting these data to the AP, and finally the AP delivers the data to a data center in a hospital. Since the AP is usually connected to the Internet via cables, we do not consider this part in this paper. In the experiment, we use one TelosB mote instead of three motes, a laptop connected with a TelosB mote via USB as an aggregator, and an AP connected with Internet through cables, which are the same experimental devices and settings as in [28]. We collect about 20-minute PDR traces with settings that the aggregator transmits polling message every 20ms and

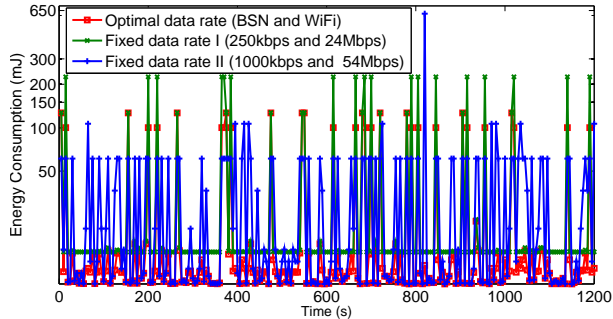


Fig. 5: Energy Consumption Comparison

calculates the PDR values every 5 seconds. Then based on the SNR-PDR mappings, we convert PDR traces into SNR traces for performance evaluation of optimal data rate solution.

B. Energy Savings

In order to show the energy savings of the data rate adaptation solution, we compare our optimal solution with the fixed data rate solutions. Our optimal solution works through the aggregator selecting optimal data rates from the loaded table according to the SNR traces for motes and itself. However, the fixed data rate solutions operate by the mote and aggregator transmitting packets with prefixed data rates without considering the current SNR values. In particular, for the fixed data rate solutions, we directly use collected PDR traces. In this way, we guarantee that all the solutions are based on the same trace data.

Since available data rates in the BSN are $r_{BSN} : \{250kbps, 500kbps, 1000kbps, 2000kbps\}$ and in the WiFi network are $r_{WiFi} : \{6Mbps, 12Mbps, 18Mbps, 24Mbps, 35Mbps, 48Mbps, 54Mbps\}$, we randomly choose $250kbps$ for the BSN and $24Mbps$ for the WiFi network and $1000kbps$ and $54Mbps$ as two fixed data rate solutions for energy consumption comparison. We plot the energy consumption of optimal data rate solution and the two fixed data rate solutions based on the SNR traces. As illustrated in Figure 5, the optimal data rate solution consumes the least energy comparing with the two fixed data rate solutions. Moreover, the fixed data rate combination ($250kbps, 24Mbps$) consume more energy than the combination ($1000kbps, 54Mbps$). Compared with fixed data rates I and II in Figure 5, the optimal data rate solution saves 35% and 30% energy, respectively.

Furthermore, we compare the optimal data rate solution with more fixed data rate solutions in terms of the mean energy consumption and energy savings. The results are tabulated as shown in Table III, with columns representing data rates r_m in BSN, r_a in WiFi networks, the Mean(E) energy consumption and Energy Savings. The energy savings in each row are calculated as the energy that the optimal data rate solution saves over the energy that the corresponding fixed data rate solution consumes. As shown in Table III, overall, the optimal data rate solution consumes the least energy $22.6mJ$ and achieves up to 86% energy savings comparing with all the

r_m (kbps)	r_a (Mbps)	Mean (E) (mJ)	Energy Savings
250	6	39.1	42%
250	24	35.4	36%
250	54	34.6	35%
500	18	57.7	61%
500	54	56.6	60%
1000	12	34.2	34%
1000	48	32.4	30%
2000	54	171.6	86%
Optimal Data Rate		22.6	N/A

TABLE III: Performance Comparison

fixed data rate solutions. An interesting observation is that for the same r_m value, the fixed data rate solution with higher r_a value consumes less energy and the energy savings of optimal data rate solution decreases with the increase of r_a . For example, the mean energy consumption and energy savings in the first three data rows gradually decrease with the increase of r_a . The reason is that the same amount of data transmitted from motes consume less energy if r_a is higher. Another observation is that for the same r_a value, the fixed data rate solution with higher r_m value consumes more energy and the energy savings of optimal data rate solution increases with the increase of r_m . For instance, the mean energy consumption and energy savings in the third, fifth and eighth rows increase with the increase of r_m . This is because more data generated by higher data rate r_m consumes more energy to transmit packets. Therefore, we obtain the conclusion that the optimal data rate solution saves energy by dynamically adjusting the joint data rates of BSN and WiFi networks to current SNR values.

VII. CONCLUSION

In this paper, we present the total communication energy consumption optimization for both BSN and WiFi networks through the joint data rate adaptation. More specifically, we first propose the BSN-WiFi network system in four consecutive phases in detail. With this system, we analyze the communication energy consumption, throughput and time delay, and SNR-PDR mappings for BSN and WiFi networks, respectively. Then, based on the analysis, we build an energy optimization model with constraints of SNR-PDR mappings, throughput, and time delay to minimize the total energy consumption in BSN-WiFi networks. We demonstrate that the model is a GP problem and can be solved by *cvx*. With the input of SNR values, by solving this model, we obtain the output of optimal data rates associated with SNR values, which are then tabulated for online data rate adaptation. Finally, we collect 20-minute traces from the specific BSN-WiFi network system for performance evaluation, and the results demonstrate that our optimal data rate solution achieves up to 86% energy savings comparing with the solutions using fixed data rates.

ACKNOWLEDGMENT

This work was supported in part by US National Science Foundation (Grant nos. ECCS-0901437, CNS-0916994), the National Natural Science Foundation of China (Grant nos. 61173178, 61070246, 61003247), the Program for New Century Excellent Talents in University of China (Grant nos. NCET-09-0838, NCET-08-0603), the Fundamental Research Funds for the Central Universities (Grant nos. CDJZR10180002, CDJZR10180003, CDJZR10180010), and the Natural Science Foundation Project of CQ CSTC (Grant nos. 2010BB2047, 2010BB2210, 2009BB2211).

REFERENCES

- [1] J. Chen, K. Kwong, D. Chang, J. Luk, R. Bajcsy, "Wearable sensors for reliable fall detection," in *Proc. IEEE EMBS'05*, 2005.
- [2] O. Chipara, C. Lu, T. Bailey, G.C. Roman, "Reliable Clinical Monitoring using Wireless Sensor Networks: Experience in a Step-down Hospital Unit," in *Proc. ACM SenSys'10*, 2010.
- [3] G. Holland, N. Vaidya, P.Bahl, "A Rate-Adaptive MAC Protocol for Multi-Hop Wireless Networks," in *Proc. IEEE MobiCom'01*, 2001.
- [4] M. Keally, G. Zhou, G. Xing, J. Wu, A. Pyles, "PBN: Towards Practical Activity Recognition Using Smartphone-Based Body Sensor Networks," in *Proc. ACM SenSys'11*, 2011.
- [5] A. Pyles, Z. Ren, G. Zhou, X. Liu, "SiFi: Exploiting VOIP Silence for WiFi Energy Savings in Smart Phones," in *Proc. ACM Ubicomp'11*, 2011.
- [6] F. Albinali, S. Intille, W. Haskell, M. Rosenberger, "Using Wearable Activity Type Detection to Improve Physical Activity Energy Expenditure Estimation," in *Proc. ACM Ubicomp'10*, 2010.
- [7] J. Cranshaw, E. Toch, J. Hong, A. Kittur, N. Saleh, "Bridging the Gap Between Physical Location and Online Social Networks," in *Proc. ACM Ubicomp'10*, 2010.
- [8] Q. Li, J.A. Stankovic, M.Hanson, A. Barth, J.Lach, G. Zhou, "Accurate, Fast Fall Detection Using Gyroscopes and Accelerometer-Derived Posture Information," in *Proc. ACM BSN'09*, 2009.
- [9] T. Gao, C. Pesto, L. Selavo, Y. Chen, J. Ko, J. Lim, A. Terzis, A. Watt, J. Jeng, B.R. Chen, K. Lorincz, M. Welsh, "Wireless medical sensor networks in emergency response: Implementation and pilot results," in *Proc. IEEE HST'08*, 2008.
- [10] S. Lanzisera, A.M. Mehta, K.S.J. Pister, "Reducing Average Power in Wireless Sensor Networks Through Data Rate Adaptation," in *Proc. IEEE ICC'09*, 2009.
- [11] B. Fateh, M. Govindarasu, "Energy-Aware Adaptive MAC Protocol for Real-Time Sensor Networks," in *Proc. IEEE ICC'11*, 2011.
- [12] P.S. Khaimar, N.B. Mehta, "Power and Discrete Rate Adaptation for Energy Harvesting Wireless Nodes," in *Proc. IEEE ICC'11*, 2011.
- [13] F. Martelli, R. Verdone, C. Buratti, "Link Adaptation in IEEE 802.15.4-based Wireless Body Area Networks," in *Proc. IEEE PRIMRC Workshops'10*, 2010.
- [14] F. Martelli, R. Verdone, C. Buratti, "Link Adaptation in Wireless Body Area Networks," in *Proc. IEEE VTC Spring'11*, 2011.
- [15] A. Kamerman, L. Monteban, "WaveLAN-II: A High-Performance Wireless LAN for the Unlicensed Band," *Bell Labs Technical Journal*, vol.2, no.3, pp.118-133, 1997.
- [16] M. Lacage, M.H. Manshaei, T. Turletti, "IEEE 802.11 Rate Adaptation: A Practical Approach," in *Proc. ACM MSWIM'04*, 2004.
- [17] D. Qiao, S. Choi, "Fast-Responsive Link Adaptation for IEEE 802.11 WLANs," in *Proc. IEEE ICC'05*, 2005.
- [18] J. Bicket, "Bit-rate Selection in Wireless Networks", M. Eng. thesis, Massachusetts Institute of Technology, Massachusetts, USA, 2005.
- [19] J. Kim, S. kim, S. Choi, D. Qiao, "CARA: Collision-Aware Rate Adaptation for IEEE 802.11 WLANs," in *Proc. IEEE INFOCOM'06*, 2006.
- [20] C. Chen, H. Luo, E. Seo, N.H. Vaidya, X. Wang, "Rate-adaptive Framing for Interfered Wireless Networks," in *Proc. IEEE INFOCOM'07*, 2007.
- [21] G. Judd, X. Wang, P. Steenkiste, "Efficient Channel-aware Rate Adaptation in Dynamic Environments," in *Proc. ACM MobiSys'08*, 2008.
- [22] J. Zhang, K. Tan, J. Zhao, H. Wu, Y. Zhang, "A Practical SNR-Guided Rate Adaptation," in *Proc. IEEE INFOCOM'08*, 2008.
- [23] M. Vutukuru, H. Balakrishnan, K. Jamieson, "Cross-Layer Wireless Bit Rate Adaptation," in *Proc. ACM SIGCOMM'09*, 2009.
- [24] Z. Dou, Z. Zhao, Q. Jin, O. Yang, "Energy-Efficient Rate Adaptation for Outdoor Long Distance WiFi Links," in *Proc. IEEE INFOCOM Workshop'11*, 2011.
- [25] C. Won, J.H. Youn, H. Ali, H. Sharif, J. Deogun, "Adaptive Radio Channel Allocation for Supporting Coexistence of 802.15.4 and 802.11b," in *Proc. IEEE VTC'05*, 2005.
- [26] J. Huang, G. Xing, G. Zhou, R. Zhou, "Beyond Co-existence: Exploiting WiFi White Space for ZigBee Performance Assurance," in *Proc. IEEE ICNP'10*, 2010.
- [27] C.J.M. Liang, N.B. Priyantha, J. Liu, "Andreas Terzis Surviving Wi-Fi Interference in Low Power ZigBee Networks," in *Proc. ACM SenSys'10*, 2010.
- [28] Y. Li, X. Qi, Z. Ren, G. Zhou, D. Xiao, S. Deng, "Energy Modeling and Optimization through Joint Packet Size Analysis of BSN and WiFi Networks," in *Proc. IEEE IPCCC'11*, 2011.
- [29] B. Sadeghi, V. Kanodia, A. Sabharwal, E. Knightly, "Opportunistic Media Access for Multirate ad hoc Networks," in *Proc. ACM MobiCom'02*, 2002.
- [30] J. Corbet, A. Rubini, G.K. Hartman, *Linux Device Drivers*, 3rd ed., Sebastopol, Canada: O'Reilly Media, Inc., 2005.
- [31] *Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications*, IEEE Std. 802.11, 2007.
- [32] G. Zhou, Q. Li, J. Li, Y. Wu, S. Lin, J. Lu, C.Y. Wan, M.D. Yarvis, J.A. Stankovic, "Adaptive and Radio-Agnostic QoS for Body Sensor Networks," *ACM Transactions in Embedded Computing Systems*, vol.10, no.4, Article 48(Nov. 2011), 34 pages.
- [33] Z. Ren, G. Zhou, A. Pyles, M. Keally, W. Mao, H. Wang, "BodyT2: Throughput and Time Delay Performance Assurance for Heterogeneous BSNs," in *Proc. IEEE INFOCOM'11*, 2011.
- [34] *Wireless Medium Access Control (MAC) and Physical Layer (PHY) specifications for Low-Rate Wireless Personal Area Networks (LR-WPANS)*, IEEE Std. 802.15.4, 2003.
- [35] M. Sha, G. Xing, G. Zhou, S. Liu, X. Wang, "C-MAC: Model-driven Concurrent Medium Access Control for Wireless Sensor Networks," in *Proc. IEEE INFOCOM'09*, 2009.
- [36] L. Verma, S. Kim, S. Choi, S.J. Lee, "Reliable, Low Overhead Link Quality Estimation for 802.11 Wireless Mesh Networks," in *Proc. IEEE WiMesh'08*, 2008.
- [37] D. Halperin, W. Hu, A. Sheth, D. Wetherall, "Predictable 802.11 Packet Delivery from Wireless Channel Measurements," in *Proc. ACM SIGCOMM'10*, 2010.
- [38] J. Polastre, R. Szewczyk, D. Culler, "Telos: Enabling Ultra-Low Power Wireless Research," in *Proc. ACM/IEEE IPSN'05*, 2005.
- [39] S. Boyd, L. Vandenberghe, *Convex Optimization*, ISBN 978-0-521-83378-3, UK: Cambridge University Press, 2004.
- [40] M. Grant and S. Boyd. (2012) *cvx Users' Guide for cvx version 1.22*. [Online]. Available: http://cvxr.com/cvx/cvx_usrguide.pdf