A Wireless Communication Selection Approach to Minimize Energy-per-bit For Wearable Computing Applications

Vitali Loseu*, Hassan Ghasemzadeh† and Roozbeh Jafari*
* Department of Electrical Engineering
University of Texas at Dallas, Richardson, Texas 75080-3021
{vitali.loseu, rjafari}@utdallas.edu
† West Wireless Health Institute
10350 N. Torrey Pines rd., La Jolla, CA 92037
hghasemzadeh@gmwhi.org

***Abstract*—Body Sensor Networks (BSN) provide a way to gather continuous observations of human movements, which has a potential of improving medical care quality, and enabling continuous remote patient monitoring. Despite their potential, BSNs face serious werability constraints. Energy optimization is essential since werability is most affected by the battery size of the device. In this paper, we introduce a burst communication technique that takes advantage of data buffering to achieve lower energy-per-bit cost with a possibly higher packet size or more energy efficient communication scheme suited for higher data rates. Our energy model combines the knowledge of the signal processing required to complete a task with the deadline associated with that task to define the optimal burst transmission schedule. Based on the selected energy model, we formulate an optimization function that minimizes the overall energy cost of communication for a given signal processing task. We demonstrate the effectiveness of our approach in sway monitoring BSN applications with a short, medium, and long deadlines. We further demonstrate the relationship between the task deadline extension and the energy cost of the system. Our results show that the proposed approach can improve the cost of communication $85-95\%$ compared to streaming data to the basestation as it becomes available.**

I. Introduction

Wearable computers with sensors, also called Body Sensor Networks (BSNs), have received tremendous attention in recent years. These systems enable various applications from medical monitoring [1] to wellness [2] and sports training [3]. While very portable and inexpensive, BSN systems demonstrate effective results similar to classical systems like ambulatory equipment, motion capture, and mechanical sports training devices. Despite their considerable potential to impact our everyday's life, BSNs still face a number of challenges that need to be addressed before a wide deployment. The form factor is one of the main consideration for a successful BSN deployment. While subjects may be able to tolerate bulky uncomfortable devices during short experiments, BSN nodes need to be as seamless as possible for long term use, since smaller BSN nodes enhance the werability and comfort.

A typical BSN node contains sensors, processing, wireless, battery and often storage units. Due to a relatively slow advancement of the battery technology compared to the improvement of the processing and memory units [4], the form factor of the system is often dominated by the size of the battery. It is perceived that wireless communication often uses one order of magnitude more energy than the processors [5], emphasizing the importance of the power optimization in that area. Several efforts have been made to reduce the power consumption by optimizing RF circuits [6], [7], activating and deactivating communication blocks [8] and reducing the size of communicated data by means of signal processing [9]. Transmitting data in bursts is an efficient power saving approach in wireless sensor networks. It can reduce complexity of communication, lower energy consumption, and increase system throughput [10]. Intuitively, data are accumulated in buffers and transmitted in bursts at a higher data rate. Different radios are optimized for different data rates. Since we intend to locally manipulate the communication data rate, a look at different communication schemes is required.

Due to a great interest in low power wireless sensor networks, there have been several low power communication circuits and protocols proposed, where each has been optimized for specific applications and bit rates [11], [12]. ZigBee [13], Bluetooth [14], WiFi [15], Ultra Wide Band (UWB) [16] are among the most widely used communication standards. Among the aforementioned, ZigBee seems to be the least power consuming wireless technology; however, it is designed for a nominal bit rate of 250 Kbps and less. If the power budget per bit is considered, ZigBee does not necessarily provide the most effective method of communication. Several diagrams in Figure 1 support this claim. As shown in Figures 1(a) and 1(b), the amount of energy per bit (EPB) decreases as data rate grows. Figures 1(c) and 1(d) show the total energy as a function of data rate for ZigBee and Bluetooth technologies. For visualization, the graphs in Figures 1(c) and 1(d) are shown only for data rates 0-100 bps and 10^5-10^6 bps for ZigBee and Bluetooth, respectively. State of the art devices often provide multiple wireless communication schemes and protocols [17], [18] to improve the versatility of the overall system. The idea of the burst communication can be combined with utilization of the multiple radios at the node side to further improve the energy efficiency.

From the application perspective, body worn and implantable sensors may be required to process the sensor data within a predetermined deadline. The deadline can range from a few milliseconds, in case of a cardiac arrest, to hours, and possibly days for applications that require reporting non-urgent events to the caregivers. For example, medical staff may be interested in monitoring the number of sit to stands throughout the day, and the final report is to be collected at the end of the day or even the week. We propose to exploit this property to further reduce the power consumption of the wireless communication block for body-worn and implantable sensors. Instead of transmitting outgoing data streams immediately upon availability, we propose to store them locally and choose the most power optimized radio that does not violate the timing constraints of the application. The local storage can be realized by means of buffers. In particular, we illustrate a methodology for communication power optimization that minimizes energy per bit.

II. Related Works

BSNs generally do not require a data flow to warrant usage of a high throughput protocol. In order to justify effective usage of a high data throughput protocol, data has be accumulated at individual nodes, which means that the problem of finding the most power optimized set of radios for a specific application can be mapped into finding the best set of delays at individual nodes. This problem also can be interpreted as a problem of the optimized communication scheduling. While the problem of scheduling in a distributed hard real-time systems is known to be NP-hard [21], the problem we are considering introduces an additional level of complexity with the data flow dependencies. In the literature, there are two types of approaches to such a problem. First, an off-line scheduling solution can be considered [22]. Such protocols assume either full or almost full knowledge of the system execution, which allows to create an optimized schedule based on the available prediction. Since the problem is NP-hard, even off-line scheduling algorithms are based on heuristic solutions. The second type of approach, on-line scheduling techniques, are known to perform very poorly for the distributed hard real-time systems. In this paper we consider signal processing flow that is well defined. As a result, we can fully predict system behavior and, therefore, utilize and off-line scheduling approach.

We consider a scheduling problem applied to signal processing with data dependencies. There is a variety of heuristics that can solve this problem with a different degrees of precision and a different cost. In the field of dynamic scheduling of work flow application on the grid, well defined cycle estimation and task migration techniques can be used to come up with good scheduling heuristics for a Directed Acyclic Graph (DAG). Effective scheduling in VLIW machines can be achieved with the help of intelligent software pipelining that takes advantage of the software dependencies [23]. A similar idea is applied in effective instruction scheduling for pipelining [24], where a DAG based heuristics are used to reduce the number of pipeline interlocks. The uniqueness of the problem, we are considering, lies in the fact that it needs to schedule data delays; scheduling a delay does not only affect the specific processing block, but also every processing block after it. An effective scheduling technique that accounts for this delay prorogation would allow for efficient burst communication.

The idea of data aggregation for energy savings has been used extensively in different contexts. When sensor nodes are forwarding data to a central node or a set of nodes, packets of multiple flows can be combined to create larger joint packets [25], [26]. This idea is known as data centric routing [27], and has proven very useful in the setups similar to BSNs that use a star topology for communication. A similar idea can be applied for query processing. Instead of aggregating the data from the sensor nodes, it is possible to aggregate requests for such data, which would force those queries to be processed in large chunk [28]. Our approach differs from all of the above because we aim to delay particular data flows, instead of combining multiple data flows to achieve energy savings. This idea has been explored in the past; however, authors of [29] did not consider application deadlines. We consider that a given network flow supports specific applications with deadlines.

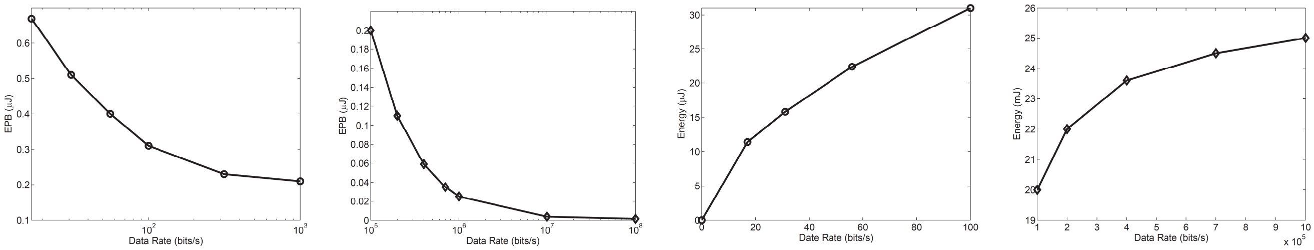
III. Preliminaries

Before defining the problem formulation, we first introduce some preliminary concepts including the application considered in this paper, signal processing and the energy models relevant to the formulation.

A. Energy Cost Model

During the execution, nodes in a BSN spend energy on collecting data from the sensors, storing the incoming data, and forwarding it to the base station. The energy cost of the sensor operation depends on the particular hardware, and the demands of the application. We assume that for our applications the cost of processing is constant. There is a variety of memory types that offer different read/write costs for different capacities. However, our energy model does not consider the energy cost of memory operation due to the memories like FeRAM providing non-volatile read and write costs orders of magnitude below the cost of communication [32]. Additionally, there is a variety of low power communication protocols that are designed to provide different system throughput at different energy-per-bit cost. We next consider a set of wireless modules and trade-offs they can offer in a BSN application.

1) Communication Energy Cost: In this work, we consider four types of wireless protocols, namely ZigBee [13], Bluetooth [14], WiFi [15], and Ultra Wide Band (UWB) [16]. The considered radio protocols operate on 10 - 100 meter radius, which makes them perfectly suitable for BSN applications [30]. While these protocols have some additional differences, such as basic cell organization, encryption and authentication capability, and coexisting mechanism, in this paper we focus



(a) EPB (ZigBee) (b) EPB (Bluetooth) (c) Energy (ZigBee) (d) Energy (Bluetooth)

Fig. 1. Energy per bit (EPB) and total energy cost versus data rate for ZigBee and Bluetooth (based on energy models in [19] and [20])

TABLE I
TYPICAL PARAMETERS FOR WIRELESS PROTOCOLS (BASED ON FINDINGS IN [30], [31])

	Bluetooth	ZigBee	UWB	WiFi
Max. Packet Size (bytes)	339	102	2044	1600(2312)
Max. Data Rate (Mbps)	.72	.25	110	54
Energy per 1Kb (mJ)	0.034	0.296	0.007	0.013

TABLE II
LOW POWER OPERATION CHARACTERISTICS [30], [31]

	Bluetooth	ZigBee	UWB	WiFi
TX Current	57mA	24.7mA	~230mA	219mA
RX Current	47mA	27mA	~230mA	215mA
Sleep Current	15μA	400nA	.5mA	10mA
V_{dd}	3.3V	3V	3.3V	3.3V

on the differences in the bit rate and energy cost of the communication. Currently, ZigBee and Bluetooth are the most popular BSN wireless protocols. This is mostly due to the application demand to forward data as soon as it becomes available. This approach is best realized with the protocols that use lower data transmission rates. In order to operate at a higher rate, nodes need to accumulate data before the transmission. Table I shows that typically both WiFi and UWB have packet sizes almost one order of magnitude larger than ZigBee and Bluetooth. At the same time, if a sufficiently large packet can be accumulated, it is clear from Table I that using WiFi or UWB can constitute significant energy savings.

TABLE III
POWER-UP CHARACTERISTICS [33], [20], [34], [35]

	Bluetooth	ZigBee	UWB	WiFi
Startup Current	5.5mA	0.4μA	5.3mA	37.9μA
Startup V_{dd}	2V	1.8V	1.5V	3.3V
Startup Time	120μs	970μs	3.5ns	2s

When considering a system that is equipped with multiple radios for communication, it is important to discuss the behavior of each radio when it is not being used and a possible energy cost associated with it. When a radio is not used, there are two possible strategies to reduce energy consumption. First, the radio can enter a low power mode, which greatly decreases the operation current of the device and therefor the energy expenditure. Table II includes reference values for low power operation of the radios considered in this paper. While the low power mode energy is significantly lower than the operational energy expenditure, it may not be a good solution in a system with infrequent use of the radio. Table III displays the cost of the radio manipulation. This table clearly demonstrate that over time while low power operation seems to be more effective, the energy cost of the low power mode exceeds the cost of turning the radio off. While turning the radio off is relatively costly, it is approximately equal to idle mode operation for $25ms$. It suggests that with a short time between transmissions it is beneficial to maintain low power mode, while for the longer time between transmissions turning the radio off is the better choice.

B. Pilot Applications

BSNs can be employed in a variety of monitoring tasks. These tasks have different resource demands, priorities, and deadlines. In this paper we consider a few variations of the sway analyses application. We first consider the fall detection application. In this application inertial sensors can be used to detect the amount of postural sway to predict likelihood of falls [36]. When a fall becomes likely, the postural sway of the upper body needs to be quantified. Furthermore, this information has to be relayed to the subject as soon as possible, which makes it an application with a very high priority and short deadline. In case of fall prevention, the application may need to produce a result in the matter of $20ms$. While in the case of the fall detection, a deadline of a $2-3s$ is acceptable. In both cases, the system needs to communicate the raw data of the incident. Second, we consider an application that can improve the quality of the fall detection. It has been suggested that the amount of sway to cause a fall is not static and varies depending on the level of activity in a person's lifestyle [37]. This suggests that, that to avoid errors in the fall prediction application, the system needs to constantly monitor the amount of activity in patient's life. As a result, this application may also have a deadline of $30min$ to $1hour$. This application does not require the sensor nodes to forward all of the observed raw data to the base station. Instead, the basestation can maintain an average data set that represents the amount of activity over time. This application can be employed in a long term patient monitoring. It can identify time intervals where subject's sensor reading significantly differ from the long time averages, and notify medical staff of the abnormalities.

IV. Problem Statement

BSN applications can be defined with a DAG that describes the collaborative signal processing of the nodes in the network, and a deadline that defines the time to complete the processing associated with the application. The simplest communication method assumes data to be processed and output forwarded to other nodes as soon as they are received. Energy efficiency of this approach can be improved by utilizing more effective radios for communication. Figure 1 shows that higher data rate protocols have a lower energy-per-bit cost. To achieve energy efficiency data can be communicated and sent out in bursts at different nodes. To accumulate enough data for the burst communication, delays can be introduced at all of the nodes in the communication model. Therefore, the problem of optimizing communication energy for a given application becomes equivalent to identifying the best set of delays and the respective set of communication protocols at individual nodes in the DAG without violating the timing constraints of the application.

A. Problem Motivation

Each application A in the system is defined with a dependency graph $G = (V, E)$, a set of sensor nodes V, a set of communication dependencies $E = \{r_{ij}\}$ between the nodes in V, a set of source nodes V_{source}, a set of destination nodes V_{dest}, a set of deadlines T_d associated with the destination nodes V_{dest}. To simplify the notation, we introduce a single source node V_S with an infinite capacity links to nodes in V_{source}, and a single destination node V_D with outgoing links from the nodes V_{dest} terminating at it. Define max(T_d) to be the maximum amount of time that data can be delayed between V_S to V_D. To account for the delays at individual nodes, we define d_i to be the cumulative delay at V_i, meaning that any data byte can be transmitted by V_i no sooner than d_i seconds after leaving V_S. To accommodate all of the data accumulated at V_i we define a buffer b_i at each node V_i. The size of b_i can be calculated as

$$b_i = \sum_j d_i \times r_{ij}, \forall\ r_{ij} \in \text{ E} \tag{1}$$

r_{ij} is defined as the link capacity, governed by the application, d_i is defined as the lower bound of the delay because it is possible that at time d_i the data may not yet be available at V_i. If data arrives at V_i later than d_i seconds after leaving V_S, it is transmitted by V_i immediately. However, regardless of whether the data is slowly accumulated at V_i or is received in one transmission, b_i represents the new outgoing link from V_i. The cost of transmitting the buffer data is defined as

$$e_i = f(b_i) \tag{2}$$

where $f(x)$ is the cost of sending x units of data. The detailed definition of $f(x)$ will be provided in Section IV-C.

In order to satisfy the timing requirements, the system needs to ensure that the cumulative delay at V_D does not exceed the deadline associated with the packets to be delivered. In our optimization delays are assigned independent of each other. This means that the individually computed delay at V_D can be defined by either d_D or by any other d_i that precedes d_D on the data path from V_S and exceeds it. It is true, since the communication takes place when the buffer, defined with the help of the value of the delay, is full. If V_j has a smaller delay, and therefore smaller buffer than V_i, its buffers will be flooded upon receiving a communication from V_i, which will cause immediate data transmission from V_j. In this example, the delay of V_j does not contribute to the overall delay of the data in the system. Therefore, the deadline constraint can be defined as

$$max(d_i) \leq T_d, \forall\ V_i \in \text{ V} \tag{3}$$

The overall objective of the optimization is to find the best set of delays that allow minimization of the energy expenditure of an application A via utilizing more efficient communication protocols at the nodes in the network without violating the timing constraints.

$$\begin{aligned} &\text{minimize } \sum e_i \\ &\text{subject to: } \max(d_i) \leq T_d, \forall\ V_i \in \text{ V} \end{aligned} \tag{4}$$

B. Problem Complexity

Our formulation is similar to a knapsack problem, since it attempts to pack delays at different nodes into a deadline of the application. However, there is a major difference between the two problems, in the traditional knapsack problem the size and the benefit/cost of items is constant and is independent of each other. That is not the case in our problem, since the delay that propagates through the path from V_S to V_D also changes benefit/cost values of the following node's delays. This implies that our system needs to consider an exponential number of choices for the delay values. If the considered problem can be solved easily, a similar solution can be applied to the knapsack problem, which is known to be NP-complete [38]. In this paper we solve the problem using enumeration of the possible solutions using an integer linear programming (ILP) solution in order to demonstrate usefulness of this type of the optimization in BSNs. It is a reasonable approach since the number of solutions to consider depends on the length of the path from the source nodes to the destination nodes, which in BSN applications is typically is 2 or 3 with less than 10 nodes in the system.

C. Problem Formulation

We first define the energy cost of sending data using each one of the four wireless protocols, assuming that each protocol sends data using the maximum packet size. We use the packet size of 1600 for WiFi in order to make it competitive with UWB. $cost_j$ corresponds to the energy-per-bit values defined in Table I for each of the four protocols. The energy cost of sending x units of data at V_i can then be defined as

$$e_i(x) = cost_j \times x \times c_{ij} \tag{5}$$

where c_{ij} takes a value of either zero or one, and selects whether the specific protocol is used for communication. The overall linear objective function can be defined as

$$minimize \sum_i \left(cost_j \times \sum_k r'_{ik} \times c_{ij} \right), \forall r_{ik} \in E \tag{6}$$

where r'_{ik} corresponds to the modified data flow after data has been delayed at V_i in terms of bits per second.

First, we consider a situation where nodes accumulate enough data to send one maximum size packet using each radio. As a result the delay d_i at each node V_i can be defined as

$$d_i = \frac{p_j}{\sum_k r_{ki}} \times c_{ij}, \forall r_{ki} \in E \tag{7}$$

where p_j is the maximum packet size value defines for each protocol in Table I.

Based on the discussion in Section IV-A, the system needs to identify the largest delay in the system and guarantee that it does not exceed the deadline. This can be done with introduction of the following constraint

$$\max\ d_i \leq T_d, \forall i \in V \tag{8}$$

but since this construct can be expressed in this form in our ILP formulation, we replace it with (9) since they are logically identical.

$$d_i \leq T_d, \forall i \in V \tag{9}$$

This definition of d_i generates a solution, where each node accumulates data until the size of the suitable packet for each radio, as shown in Table 1, is reached. We can chose to send the packet immediately and wait until the next packet is generated. During the waiting time, the node can be switched into the low power mode. The other alternative is to accumulate data for more than one such packet, send multiple packets in bulk, and turn the radio off until the next set of packets becomes available. Hence, we introduce a coefficient l in our formulation, that defines the number of packets to be accumulated, to group multiple packets into P_{jl}.

$$P_{jl} = l \times p_j \tag{10}$$

Taking (6), (7), (8), and (10) into account, the overall solution can be defined as

$$min \sum_i \left(cost_i \times \sum_k r_{ij} \times c_{ij} \right), \forall r_{ik} \in E, \forall l \tag{11}$$

$$\text{subject to: } c_{ij} \in \{0,1\}$$

$$\sum_{j=0}^{4} c_{ij} = 1, \forall i \in V$$

$$\frac{P_{jl}}{\sum_k r_{ki}} \times c_{ij} \leq T_d, \forall r_{ki} \in E$$

D. Optimality Discussion

In reality, there is a number of delay set solutions that are not practical. This observation comes from the fact that delaying data at node V_i causes that node's output to be modified, while the following nodes estimate their delays based on the original output of V_i. The new output r'_{ij} can be defined in terms of the original output, and the delay applied of the node.

$$r'_{ij} = r_{ij} + d_i \times r_{ij} \tag{12}$$

Once the optimization decides to introduce a delay d_i to V_i, its output is modified to r'_{ij} every d_i seconds. However, V_j still estimates to receive r_{ij} every second and calculates d_j based on this estimation. Due to the propagation error not all of the data may be available at V_j at time d_j. This idea is better described in the example of Figure 2. Figure 2 shows how for every 10 points of input V_2 produces 5 units of output. Figure 2.a shows a sample signal processing flow with no data delays. This strategy is inefficient and we may chose to delay packets to achieve a better energy per bit characteristic. This idea is further demonstrated in Figure 2.b and Figure 2.c. Figure 2.b has an example where V_1 expects to produce 20 units of data every 2 seconds, and V_2 expects to produce 20 units of data every 4 seconds. From Figure 4 it is clear that no problem arises since d_2 is a multiple of d_1, and V_2 has enough input to generate its output at multiple of d_2. This is not the case in the example of Figure 2.c. In the figure, V_1 produces 30 units of data every $3s$, while V_2 expects to produce 20 units of data based on the 40 units of input every $4s$. From Figure 5 it is clear that at time 4, V_2 has only 30 units of input. Which is not enough to produce an output at V_2. At time 6, when another set of inputs arrives from V_1, V_2 has enough data to produce the first set of outputs. The figure also shows that incorrectness of the estimation is local, and at time 12 V_2 produces 3 outputs as expected. In the next section we discuss the estimation of the delay inaccuracy in the worst case scenario.

E. Error of Delay Estimation

First, we identify the worst case error that can be introduced into the system between two nodes. An example, where the error is equal to the maximum of the two delays is trivial. Consider V_1 with a delay of k, and V_2 with a delay of 1. V_2 does not receive any input until time k and immediately

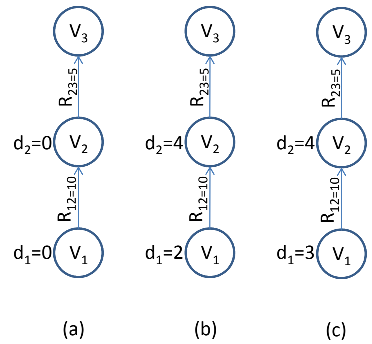


Fig. 2. Examples of Error Propagation

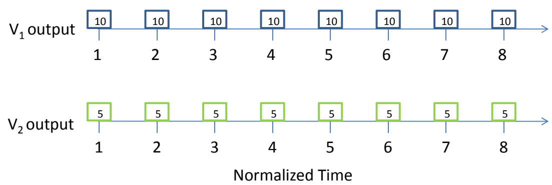


Fig. 3. Data flow in Figure 2.a

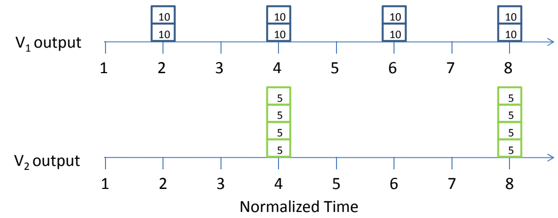


Fig. 4. Data flow in Figure 2.b

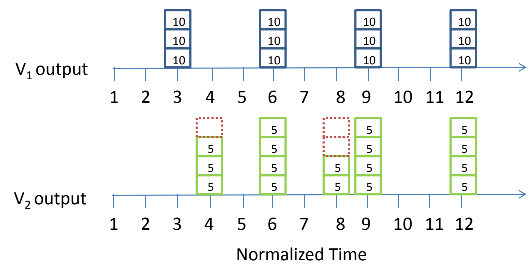


Fig. 5. Data flow in Figure 2.c

produces k outputs, which means that each output is on average delayed by k time units, which is the largest of the two delays. A stronger argument can be made

Lemma 1: In a graph with two nodes, the error of the delay estimation can not exceed the largest of the two delays.

Proof: Consider a graph with nodes V_1 and V_2, and delays d_1 and d_2 assigned to the respective nodes. Assume that the expected inaccuracy of the delay exceeds the $max(d_1, d_2)$. If the average value exceeds the $max(d_1, d_2)$, it means that during the algorithm execution data is delayed at one of the nodes for longer than the $max(d_1, d_2)$, which is impossible. Therefore, by contradiction, in a graph with two nodes, the inaccuracy of the delay estimation can not exceed the largest of the two delays. ■

Next, we consider a case with more than two nodes.

Theorem 1: In a graph with a sequence of $k + 1$ nodes, the error of the delay estimation can not exceed k times the largest of the $k + 1$ delays or $k \times max(1..k + 1)$.

Proof: For the base case consider (1). Assume that for k nodes, the inaccuracy of the delay is $(k - 1) \times max(1..k)$. Without a loss in generality, assume that if one more node is added to the sequence, the new node has the highest delay. Based on (1) the delay between k^{th} and $(k + 1)^{th}$ item can not exceed $1 \times max(k, k + 1)$. Clearly, $max(1..k + 1) = max(max(1..k), max(k, k + 1))$, which means that the total inaccuracy is defined as $(k - 1) \times max(1..k + 1)$+1 $\times$ $max(k, k + 1)$ = $k \times max(1..k + 1)$. ■

The worst case of the error in delay estimation that can be accumulated by our ILP solution might seem a major concern, however, it does not carry significant affect on the BSN applications we considered. First, BSN application normally do not involve many nodes, which limits the amount of error of the system. Movement monitoring and classification can be achieved with 1 to 4 nodes without a significant sacrifice of the classification quality.

V. Experimental Result

To demonstrate the effectiveness of our approach, we apply simulations of our optimization to the DAGs corresponding to the applications defined in Section III-B. For this experiment, we assume hardware that can simultaneously support Zigbee, Bluetooth, WiFi, and UWB radios and switch between them. We also consider a system that uses only one of the four radios at a time, while turning off the others. While a node is accumulating data, all the radios are turned off. We assume the hardware to be equipped with a low power wake-up circuitry that allows radios to know when they need to power up[39]. To avoid discrimination radios based purely on the startup cost, we consider a scenario that does not include the startup cost. We add this scenario because we feel that improvements in the wireless technology can significantly decrease that cost, especially in the case of the WiFi networking, which has at least 3 orders of magnitude inferior startup cost compared to other radios. We begin with a requirement to accumulate one packet of the largest size specified for the radio. We then increase the number of packets that needs to be accumulated before each radio can be used. Finally, we consider how changes to the deadline of an application can affect the radio selection.

First, we consider the fall prevention and detection application. For this application, two nodes are placed on the body. One node is places on upper body, while the second node is placed on the waist. The application tries to detect or even predict falls based on the amount of upper body sway exhibited by the subject. Details of the signal processing for this application is depicted in Figure 6. The values assigned to the edges of the figure correspond to the bytes-per-second

TABLE IV

FALL DETECTION APPLICATION OPTIMIZATION WITHOUT RADIO DEACTIVATION COST

T_d	N_1		N_2		N_3		Cost
(s)	Radio	d_1(s)	Radio	d_2(s)	Radio	d_3(s)	(μJ)
.2	Z	0	Z	0	Z	0	96.8
3	Z	0	B	3	B	3	23.9
7	B	7	B	3	B	3	11.1
12	B	7	W	12	W	12	5.28
15	B	7	U	15	U	15	3.61
32	W	32	U	15	U	15	2.58
41	U	41	U	15	U	15	2.29

TABLE V

FALL DETECTION APPLICATION OPTIMIZATION WITH RADIO DEACTIVATION COST

T_d	N_1		N_2		N_3		Cost
(s)	Radio	d_1(s)	Radio	d_2(s)	Radio	d_3(s)	(μJ)
.2	Z	0	Z	0	Z	0	981
3	Z	0	B	3	B	3	150
7	B	7	B	3	B	3	11.1
15	B	7	U	15	U	15	3.61
41	U	41	U	15	U	15	2.29

communication requirement. In this application, both waist and upper body nodes monitor the amount of sway and balance. When one of the nodes detects a fall, it sends data about the abnormal readings to the other node. If the second node confirms the fall classification, it affirms its decision to the original node. Both nodes start forwarding raw data to the base station, to avoid information loss, of the last few seconds before the fall was detected and a few second after the fall to the base station. The results of the optimization without radio deactivation cost are displayed in Table IV and result with the deactivation cost are displayed in Table V, where startup and shot down costs are define in Table III. In the case where the radio deactivation cost is not taken into account, if the deadline for the application completion is strict $20ms$, then the system does not have enough time to accumulate large enough packets to use anything other than the ZigBee radio. If the deadline is relaxed to $3s$, in case of the fall detection application, the system can improve the power performance a little over 4 times, and almost 40 times if the deadline can be extended to $32-41s$, in case of the long term average calculation. Practicality of such deadline extension depends on the hardness of the deadline, and the overall amount of data to be sent. Addition of the activation/deactivation cost introduces a few changes, but the main trend remains. ZigBee and Bluetooth have a relatively high activation cost, which makes the benefit of UWB stand out even more. Instead of a 40 times improvement, UWB increases energy savings to almost two orders of magnitude. Finally, WiFi has a very high activation cost, which effectively dominates the overall communication cost and removes WiFi from consideration.

We also consider the error in delay estimation that can be

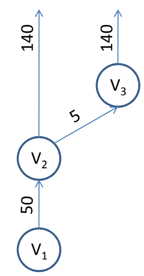


Fig. 6. Dependency Graph for Fall Detection

caused by lack of multiplicity of the delays. Table VI shows comparison of d_i, or the calculated value, to the d'_i, or the value that does not cause delay errors, for the fall prevention and detection application. d'_i is calculated by making it a product of its predecessor's delay, as long as the new delay does not violate the deadline. We also introduce a concept of $Punctuality$. This concept assumes that if nodes do not have enough data to communicate they will wait until sufficient data is available. This effectively is transformed into the smallest delay divisible by node's predecessor delays. The node is not penalized for that action, unless the first suitable delay exceeds the deadline of the application. Punctuality is defined as $(1-error/deadline)\times 100$. From the table it is clear that the real error is no more than 20% of the maximum error discussed in Secton IV-E.

TABLE VI

FALL DETECTION APPLICATION OPTIMIZATION DELAYS

T_d	N_1		N_2		N_3		Punctuality
(s)	d_1	d'_1	d_2	d'_2	d_3	d'_3	(%)
.2	0	0	0	0	0	0	100
3	0	0	3	3	3	3	100
7	7	7	3	3	3	3	100
12	7	7	12	14	12	14	92
15	7	7	15	21	15	21	80
32	32	32	15	15	15	15	100
41	41	41	15	15	15	15	100

VI. CONCLUSION AND FUTURE WORK

We utilized the fact that higher throughput radios have a lower energy per bit cost, to define an energy optimization technique that accumulates data at local nodes and then transmits them in bulk while not violating the timing constraint of the applications. To materialize this solution, we first identified the type of signal processing that is used in BSN applications. We then looked at communication and memory energy cost associated with these applications. Based on these preliminary results, we defined a problem and suggested an ILP solution to it. Since the actual problem is NP hard, we provided the worst case bound on error for BSN applications. To verify the validity of the approach, we applied it to three representative

BSN application with different deadline, amount of communicated data, and priority. We showed that our approach can improve the energy cost of communication from 20 to a 50 times depending on the particular application parameters. Our approach however has some limitations. The main problem lies in the error of the delay estimation, which potentially has a very bad worst case. We intend to investigate this issue further, and design an approach capable of maintaining the energy benefit of the proposed approach, while minimizing the bound on the delay estimation error.

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