Managing Power Consumption for IEEE802.15.4 HealthNets

Zahra Abdalla Elashaal, Mohamed H. Habaebi
Department of Computer Engineering, University of Tripoli, Libya
Email: zelashaal@yahoo.ca ; z.elashaal@uot.edu.ly
Edries Abdelhadi Ali
Faculty of Information Technology, University of Tripoli, Libya
e.gomied@uot.edu.ly

Abstract— **Nowadays, Low Rate Wireless Personal Area Networks (LR-WPAN) are used in a wide variety of embedded applications, especially in medical area and patient monitoring. The use of a wireless network system for the sensor data results provides greater flexibility for both the patient and the medical staff. Power consumption is measured while doing data transmission. Depending on the estimated distance calculated from the averaged Received Signal Strength Indicator (RSSI), the transmission power needed were computed and used for each packet transmission. Hence, instead of transmitting in full power regardless of the location of the receiving node, the transmission power is carefully controlled depending on the estimated distance.**

In this paper, A simple transmit power management scheme is introduced and evaluated by simulation. The scheme is easy to implement yet it provides excellent performance. The study highlights that, node localization and ranging techniques aside, even the use of available RSSI readings at the sensor node can be used to reduce energy consumption levels tremendously prolonging the network/battery lifetime and with tolerant reliable delivery. Results indicate payload size has a considerable effect as up to 80% improvement can be achieved when transmitting ECG signals, while only a minimal improvement can be achieved when the temperature information is transmitted.

Index Terms—**RSSI, ZigBee, HealthNet, energy efficiency, Battery, power control**

I. Introduction

Nowadays, Low Rate Wireless Personal Area Networks (LR-WPAN) are used in a wide variety of embedded applications, especially in medical area and patient monitoring in addition to home automation, industrial sensing and control, environmental monitoring and sensing. In these applications, numerous embedded devices running on batteries are distributed in an area communicating via wireless radios. IEEE 802.15.4 is a wireless standard touting great flexibility, low cost, small hardware and low power consumption. It uses the publicly available 2.4 GHz ISM band for the radio and supports a data rate of 250 kbps. In clinical diagnostics and patient's treatment, many physiological parameters, referred to as emergency vital signs or EVS such as blood gas, invasive blood pressures, pulse rate, temperature, electrocardiogram (ECG), etc, have to be detected, measured and monitored. Wireless ZigBee networks utilize digital data to enable such novel clinical applications. With the use of small portable computers at other locations within the hospital or elderly nursing home, medical staff would be able to monitor a patient regardless of her position as long as she is connected to the network. Sometimes battery operated sensors are embedded into the patient's body, hence replacing the sensor's battery is done by a surgical operation. In such scenarios, it is important to prolong the battery's life as much as possible. Extensive research works were carried out throughout the past decade into areas of localization and ranging (to provide location-based services) and tracking (to track moving targets) of wireless sensor networks (WSN) node such as ZigBee. A considerable number of these works concentrated on energy efficiency by reducing processing computation by proposing portable tiny operating systems. But to the best of the author's knowledge, none has considered the use of ranging techniques in managing the transmission power of WSN ZigBee nodes. Such a scheme is vital for any WSN node in order to survive prolonged on-patient's body operation. The use of power control for WSNs is not new, [7-10] and references therein, but the idea behind this paper is to highlight that implementing any power control mechanism, albeit simple just like what we propose in this paper or complex by utilizing localization and triangulation techniques to determine the exact distance between sender and receiver, leads to considerable energy savings especially for medical Zigbee-based WSNs with Emergency Vital Signs traffic. One way to reduce energy spent on transmission for data collected from the medical devices like ECG and body temperature is described by Messier and Finvers in [11]. Here data traffic generated by a single node was reduced when employing data compression before transmitted by using source coding for real data transmission on some nodes on the patient's body.

In This paper, a simple yet effective method that can be used to reduce power consumption of wireless sensor nodes is presented. Power consumption is measured while doing data transmission, reception or in idle state. Depending on the estimated distance calculated from the averaged received signal strength Indicator (RSSI), the transmission power needed were computed and used for each packet transmission. Hence, instead of transmitting in full power regardless of the location of the receiving node, the transmission power is carefully controlled depending on the estimated distance.

II. PROPOSED ALGORITHM & IMPLEMENTATION

A. Propagation Models Distance Estimation

Usually, the primary energy consumer in any sensor node is its radio transceiver. The exact amount of energy dissipated per transmitted or received bit is a function of distance, bit rate and transmission duration, among other factors. In order to quantify the performance of power-aware protocols, the behavior of radio wave propagation must be accurately modeled. This is a limiting factor in many network simulators, as such physical layer concerns have not been a factor in protocol design although increasingly complex models exist, which are useful in certain scenarios [1].

In embedded devices, a received signal strength indicator (RSSI) is defined using equation (1) where the reference power P_{ref} typically represents an absolute value of P_{ref}=1mW.

$$RSSI = 10.\log\frac{P_r}{P_{ref}} \quad (dBm) \tag{1}$$

The detected signal strength P_r is defined according to Friis' free space transmission equation (2), where it decreases quadratically with the distance to the sender.

$$P_r = P_t.G_t.G_r\left(\frac{\lambda}{4\pi d}\right)^2 \tag{2}$$

P_t is the transmission power of sender, P_r is remaining power of wave at receiver, G_t is transmitter antenna gain, G_r is receiver antenna gain, λ is Signal wavelength and d is Distance between sender and receiver.

The free space model predicts the mean received power distance d by representing the communication range as an ideal circle. In reality, mobile obstacles, such as human beings, vehicles, moving tree leaves, etc. may also be present. The effects of such sources on a signal are referred to as shadow fading, and result in the same signal being received at different strengths at the same distance from the transmitter. The received power at certain distance is a random variable due to multipath propagation effects, which are also known as fading effects. The log-normal shadowing model [5] is given by equation (3).

$$P_r[dBm] \cong P_t + K - 10\, n\, \log_{10}\left(\frac{d}{d_0}\right) + S \tag{3}$$

where n is Path loss exponent empirically determined by field measurement (for most 2.4 GHz applications, n = 4 to 6), d is distance from transmitter to receiver or cross-in distance, d_0 is a reference distance for the antenna far field, K is a unitless constant that depends on the environment, S is Gaussian random variable with zero mean and variance σ_S whose value ranges depending on the characteristics of the environment (for indoor environment it typically ranges from 3 to 9.6). Since sensor nodes are assumed to be placed on the patient's body and not underneath the skin, the use of a referenced point in the model placed at the start of the far-field of the sensor antenna is justifiable.

Another interesting propagation model used for determining the RSSI is the body-surface to body surface medical model for 2.4GHz presented in [2]. This model considers the variability in path loss due of the distance and frequency dependency including the body tissue for a sensor placed on the patient's body. The pathloss is given by equation (4) below.

$$RSSI\,(dB) = a\log_{10}(d) + b + S \tag{4}$$

Where a and b are coefficients of linear fitting An important note on this model is it was designed and tested for distances of maximum 5 meters only to cover a communication link between WSN nodes on the patient's body surface to an external receiver. In our study, we have assumed an extended distance to 15 meters and the extended link component of 10 meters was evaluated using the lognormal shadowing model. This is valid since the 10 meter extended link component is located within an indoor environment that is clear of body proximity and hence can be evaluated using the commonly used shadowing model.

The estimated distance $\hat{d}$ that is used to determine the transmit power levels is obtained by inverting the pathloss model as follows:

$$\hat{d} = d_0\, 10^{\left(\frac{-P_r}{P_{r0}}+S\right)/10n} \tag{5}$$

Where P_{r0} is the received power at reference distance d_0.

By setting the received power threshold, P_{rc}, a fewer *dB*s higher than the receiver sensitivity, *TxThresh* (that is the minimum power a ZigBee radio is capable of detecting and it's value is radio-specific), one can calculate the required transmit power level for the shadowing model and for the body surface medical model using equations (6) and (7), respectively.

$$\widehat{P_{t1}}[dBm] = P_{rc} - K + 10\, n\, \log_{10}\left(\frac{\hat{d}}{d_0}\right) - S \tag{6}$$

$$\widehat{P_{t2}}[dBm] = P_{rc} + a\log_{10}(\hat{d}) + b + S \tag{7}$$

In practical scenarios, the ideal distribution of P_r is not applicable, because the propagation of the radio signal is interfered with a lot of influencing effects which degrade the quality of the determined RSSI significantly. Hence a smoother envelope for the transmit power level that can be used is the averaged transmit power based on previously used transmit power level $P_{t\,i-1}$ and currently calculated transmit power level $P_{t\,cal}$ as follows:

$$P_{t\,i-avrg} = \frac{P_{t\,i-1} + P_{t\,cal}}{2} \qquad (8)$$

where, $P_{t\,i-1}$ is the transmit power for the previous packet, $P_{t\,cal}$ is the calculated power which is $\widehat{P_{t1}}$ or $\widehat{P_{t2}}$ depending on the model used if it is shadowing or medical model and $P_{t\,i-avrg}$ is the average transmit power for the current packet ready for transmission. This averaging process reduces large fluctuations in the estimated power of $\widehat{P_{t1}}$ and $\widehat{P_{t2}}$ and gives better energy efficiency, as shown in figure 1, only if the time duration (and hence $\hat{d}$ value) between consecutive cycles of transmission is not large. Otherwise, an erroneous transmit power level is used that might lead to a loss of packet. A more precise estimation of $\hat{d}$ requires the use of more sophisticated localization and tracking techniques to achieve optimal performance. Nevertheless, this simple averaging process saves the battery energy considerably, when observed over time, and does not degrade the reliability of packet delivery (throughout our simulation experiments only one ECG packet was lost). This is due, in part, to the nature of the channel, packet size, bit rate and the medical signal source itself, In addition to that, the repetitive pattern of the ECG signal with high frequency or the temperature with its slow pace of change upward or downward makes the loss of few packets insignificant.

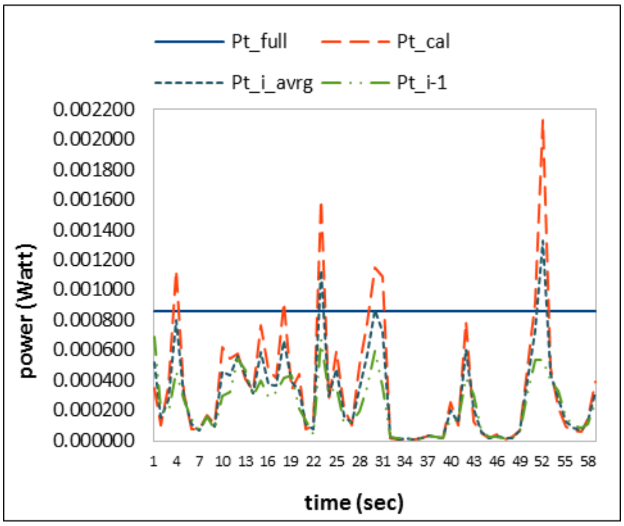


Figure 1: Average transmit power levels for two stationary nodes.

Note that when the $P_{t\,i-avrg}$ level exceeds the *Pt_full* (the maximum output level from the battery), the *Pt_full* level is used for transmission instead.

B. Battery Energy Consumption Model

To calculate the battery consumption level [6], the following relationship is used.

$$P_{t\ consum} = V_{DD} . \beta . I \qquad (10)$$

where $P_{t\ consum}$ is the Battery consumed energy in Joules for each packet transmission, V_{DD} is the Zigbee radio supply voltage and I is the transmitter circuit driving current. The parameter β is the estimator (0< β ≤1) of the circuit driving current level. Setting β to 1 lets the battery consume its maximum energy level relative to transmitting in full power.

The issue is that β is a ZigBee radio model dependent, as is the case for all WSN nodes available in the market) and its influenced by many parameters. For example, the relationship between chipcon CC2420 ZigBee radio output current and its output power is non-linear and from practical measurements reported in [3], the current is hardly stable at the output regardless of the output power level. This, in turn, leads to inaccuracy in correlating the supplied battery voltage and current with what power level is actually used for transmission. Hence, to avoid such radio model-specific issues and to generalize the solution, it is necessary to normalize β Instead of using the actual value for current in the calculation in estimating transmit power consumed in the process. Therefore, we let $\beta = \frac{\widehat{P_t}}{P_{t\,full}}$ for the models and by normalizing the maximum transmit power level $P_{t\,full} = 1$, any estimated value for $\widehat{P_t}$ will be in the range (0,1]. The energy consumption for other states such as receiving and idle were ignored in the simulation model in order to highlight the impact of transmit power level only on the battery consumption rate and on network performance and life span. The energy drained for a sent packet from the node's battery is calculated by the following formula:

$$Energy\ (Joule) = P_{t\ consum} \times Tx_{time} \qquad (11)$$

where Tx_{time} is the time needed to transmit a packet.

III. SIMULATION MODEL

NS-2 simulator with ZigBee WSN module support is used for the evaluation of the proposed algorithms. The simulation scenario is basically a 30x30 m^2 area with a mobile node-1 moving at 0.5 m/sec to imitate the patient's movement speed and a PAN coordinator node located at the center of the area, while the spectrum band of the ZigBee radios is set to 2.4 GHz frequency with Beacon enabled frame structure and a Beacon and superframe orders of 3. Other radio/channel- specific parameters, used to calculate the transmit power levels, are shown in table-1.

Table-1: Zigbee Radio Transmit power level parameters[2][3].

Parameter	Value
a	8.5
b	-12.0
K	-39.55
σ_S	4.0 dB
n	4.0
CarrierSense CSThresh	-87.34 dBm (1.84631e-12 W)
TxThresh	-82.34 dBm (5.83524e-12 W)
Sensitivity Threshold P_{rc}	-62.34 dBm (5.83524e-10 W)

A random way point (RWP) movement model is used to represent the monitored patient's movement. In this model and throughout the simulation time, the mobile node-1 chooses randomly a way point within the simulation area and moves towards it with the speed indicated above. Once arrived, it may stop for a while or repeat the process by picking another random waypoint to move to. The simulation time is set to 5 minutes and it was repeated thousands of times to average the results. Figure 2 shows a snapshot of the simulated scenario. Two traffic sources were used for the experiment, namely ECG and temperature, to represent the extreme cases of EVS signal output frequency [4]. The traffic type is Constant Bit Rate (CBR) representing the EVSs transmitted in one direction from node-1 to the PAN node. The body temperature is a very slow data rate generator compared to the ECG sensor data rate generator, where the packet size is 2 bytes only and the transmission rate is 1paket /5 sec. The ECG data source, however, generates average packet size of 100 bytes, and a transmission rate 4 packets/ sec as shown in Table-2

Table-2: Body Temperature scenario parameters

No. of nodes	2
Field size	30x30 m^2
Traffic type	CBR
Traffic flow	Node_1→ PAN Coordinator
Radio rang	15m
Duration	300 sec
Topology	Star
Data transmit	Direct
Hop count	1 hop
Temperature packt size	2 bytes
Transmit rate	1packet/ 5sec
ECG packet size	100 bytes
Transmit rate	4 packets/1sec
shadowing deviation σ_S	6.8 dB

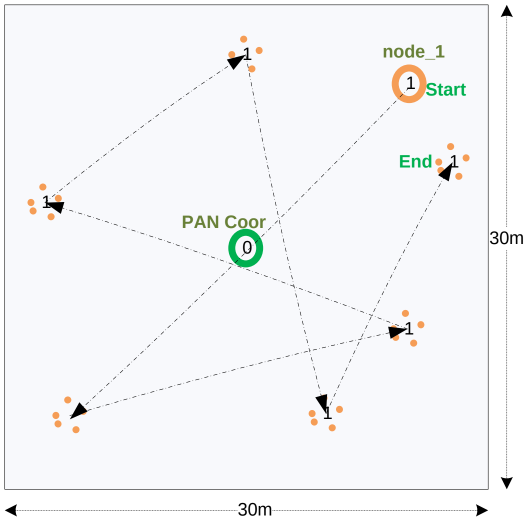
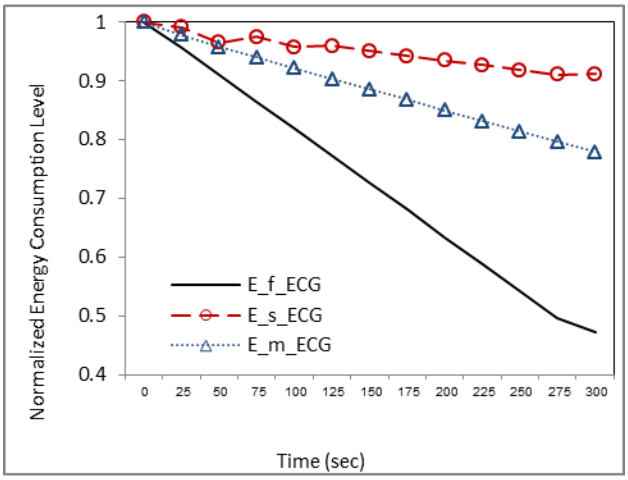


Figure 2: Snapshot of the Random way point scenario

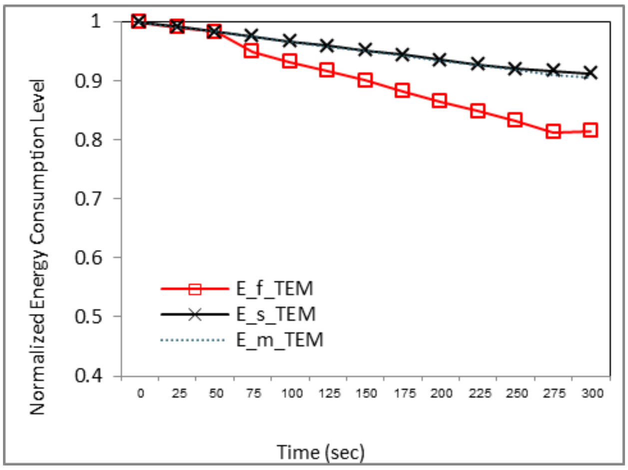
IV. RESULTS ANALYSIS

We have used many of simulation runs and averaged the results in order to evaluate the performance of the proposed power management scheme. The normalized Energy Consumption level versus time for the different propagation models and data sources using the Random way point movement scenario, are shown in figure 3 (a, b). The *E_f_ECG* and *E_f_Tem* are the normalized battery energy consumption level when the full transmit power mode is used for ECG and Temperature cases, while *E_s_ECG* and *E_s_Tem* are the normalized battery energy consumption levels produced from using shadowing model to estimate the transmit power in ECG and temperature cases, while the *E_m_ECG* and *E_m_Tem* are the normalized battery energy consumption levels produced from using the medical body surface propagation model for ECG and temperature cases, respectively.

It is clear from the results illustrated in figure 3 (a) that the amount of energy savings in the ECG case is much bigger than the energy savings in Temperature case for the same period of time. This is because the transmission rate for ECG of 4packet/1sec is much higher than temperature rate of 1packet/5sec. Obviously, ECG's high frequency of transmission is translated into an increase in battery energy savings in comparison to temperature sources. In fact, for a duration of 300 sec, an ECG node looses more than 50% of its battery energy for transmission. The same ECG node, when applying the transmit power management scheme, looses only less than 8% of its battery energy using the shadowing model and about 12% using the medical body surface model, respectively.



(a)



(b)

Figure 3: Energy consumption of all cases for the RWP scenario for (a) ECG EVSs and (b) Temperature EVSs.

The same results were confirmed in figure 3(b) using temperature instead of ECG signals as EVSs although on a much lower saving levels due to the low data rate for temperature sensors highlighting the effect of the nature of the EVS itself on the performance of the WSN node battery energy consumption level.

Nevertheless, in both cases, the shadowing model achieves the best results due to its higher accuracy in estimating the distance, and hence the transmit power levels, in comparison to the medical model or the full energy transmit model. Results obtained motivate the use of more sophisticated schemes, being proposed for localization and tracking, for communication range estimation and transmit power control. Such methodology can certainly reduce transmit energy consumption and reduce the burden on mobile sensor nodes operating in critical application scenarios such as healthnets.

V. CONCLUSION

In This work, a simple yet effective transmit power control mechanism is introduced that utilizes averaged RSSI information to reduce battery energy consumption in patient monitoring ZigBee wireless sensor networks. Two extreme cases of emergency vital signs were considered, namely, temperature and ECG signal in conjunction with different propagation models. Simulation results indicate that simple channel indicators, such as *RSSI* and/or *LQI* can be used to manage transmission power, hence reducing energy consumption considerably and prolonging network lifetime without degrading reliable delivery of EVSs. Such an approach simplifies the implementation issue into the Zigbee node protocol stack and imposes minimal computation power consumption.
The scheme performed differently under different types of vital signs highlighting the effect of EVS nature itself on the overall network performance. Large savings in battery energy were achieved for ECG signals in comparison to temperature. The scheme highlights the feasibility of using recently introduced sophisticated localization and tracking techniques to control the transmit power to prolong network lifespan and reduce interference.

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