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Lifetime Estimation of Wireless Body Area Sensor Network for Patient Health Monitoring

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***Abstract*: Wireless Body Area Sensor Networks (WBASN) is an emerging technology which utilizes wireless sensor nodes to implement real-time wearable health monitoring of patients to enhance independent living. These sensor nodes can be worn externally to monitor multiple bio-parameters (such as blood oxygen saturation (SpO_2), blood pressure and heart activity) of multiple patients at a central location in the hospital. It is important to have an estimate of the time the first node will fail in order to replace or recharge the battery because the loss of critical data is not acceptable. Simulation is used to determine the lifetime of WBASN. The lifetime of the WBASN is defined as the duration of time until the first node fails due to battery depletion. In this paper, a parametric model of a health monitoring network (HMN) is created with sets of random input distributions. Probabilistic analysis is used to determine the timing and distribution of node failure in the HMN.**

I. Introduction

PROBABILITY analysis is performed using the Monte Carlo method. This involves generating random input vectors with known distributions, and running the simulation with these vectors as input. The resulting output vectors provide the output distributions. Alternatives such as the mean value methods, generally assume a deterministic system with differentiable variables [1]. In most networked systems, the presence of discrete structures often results in discontinuities, and possibly non-monotonic responses which can result in large errors due to local minima. The use of randomized methods such as random back off in most multi-hop networks such as LEACH also results in non-deterministic behavior. Thus, the Monte Carlo method is the best option to estimate probability distributions of node failures in a WBASN.

A notable research project that addresses the needs of medical care such as node mobility, a wide range of data rates and high degrees of reliability and security is CodeBlue [2]. CodeBlue integrates sensor nodes and other wireless devices into a disaster response setting. A pulse oximeter sensor, two-lead electrocardiogram (ECG) and a specialized motion-analyzer sensor are used to collect physiological information for the prioritization of treatment by first responders.

Despite the success of CodeBlue, the concern for quality of service in terms of battery life of the WBASN is still not address in that project. A common type of failure happens when a node runs out of energy and shuts down. The timing and distribution of such failures critically impact the ability of the WBASN to collect real-time data of the physiological status of patients in a health care environment. Current approaches depend on analytical or experimental methods with expensive hardware trials. For example in [3] [4], mathematical models and hardware measurements are used to determine the lifetime of wireless sensors. However, because of many constraints imposed on sensor networks, such as energy limitation, decentralized collaboration, and fault tolerance, validation of algorithms in hardware for sensor networks tend to be quite complex and time consuming. Therefore simulation is used in this work to determine the lifetime of WBASN for health monitoring of patients.

In this paper, probability distributions of energy use and network lifetime are obtained from multiple sample runs using the Monte Carlo method. Specifically, the probability distributions of the average power consumption of each node before nodes start to fail, and distributions of nodes lost as a function of time are generated. In order to make the simulation time manageable approximation techniques are used to reduce the simulation time.

Commercially off-the-shelf (COTS) components are modeled for the simulation. The rest of the paper is organized as follows: section II explains the simulation models, input randomizations and Monte Carlo method used, the results are discussed in sections III. Finally, section IV concludes the paper and discusses future work.

II. Simulation Overview

The network is modeled in the J-Sim network simulator [7]. The architecture of the WBASN follows the J-Sim component model. J-Sim uses three top level components: the target (source) node (which produces stimuli), the sensor node (that reacts to the stimuli), and the sink (base station) node (the ultimate destination for stimuli reporting). Sensor nodes are modeled as a combination of physical components (such as CPU, battery etc.) and logical components representing the protocol stack. Each mobile node has ECG and pulse oximeter sensors that monitor heart rate and pulse oxygen respectively. When a node detects abnormal ECG or pulse stimuli beyond some threshold, it attempts to report this event to the base station. Sources produce events with random magnitudes at random intervals. Mobility and stimulus related variables are treated as random variables. Stimuli (ECG and SpO_2) are also randomly generated. The mobile nodes are implemented with Smooth Random mobility [5]. This captures mobility characteristics of temporal dependence on velocity which provides a more realistic estimation of patient mobility.

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Three routing protocols are used to test the method: A basic single-hop protocol to provide a baseline, an Ad-hoc On-demand Distance Vectoring (AODV) [6] which is an established protocol for lower density networks and a basic multi-hop protocol which assumes that each node has a GPS to determine the position of other nodes on its path to the base station.

A. Input Distributions

The input sources are in fixed positions and generate events at known distributions. The events are ECG and SpO_2 stimuli. The sources generate ECG stimuli and SpO_2 at constant intervals ΔT_s with exponential distributions. The exponential distribution was chosen because it represents a constant average rate. The sensors sample the received signals as a Gaussian process with Gaussian distributions. The Gaussian distribution is chosen because the parameters of ECG (complexes, inter-wave segments and cardiac intervals) and SpO_2 are detected independently. Once the stimuli are generated, the power of the events is added to the model. The powers of ECG and SpO_2 stimuli have a Gaussian distribution.

A further consideration that was incorporated into the HMN is mobility. The mobile wearing sensor nodes move in a preferred speed $\{V_{pref}^1, V_{pref}^2, ..., V_{pref}^n\}$, where V_{pref}^i is preferred speed of node i. The preferred speed set for each node is assumed to be random. If a node has a preferred speed set $\{0, 0.5V_{\max}, V_{\max}\}$, then the probability distribution is given by (1).

$$P(v) = \begin{cases} P(v=0)\delta(v) & v=0 \\ P(v=0.5V_{\max})\delta(v-0.5V_{\max}) & v=0.5V_{\max} \\ P(v=V_{\max})\delta(v=V_{\max}) & v=V_{\max} \\ \dfrac{1-P(v=0)-P(v=0.5V_{\max})-P(v=V_{\max})}{V_{\max}} & 0<V_{\max}<1 \\ 0 & otherwise \end{cases} \quad (1)$$

Where $P(v=0)+P(v=0.5V_{\max})+P(v=V_{\max})<1$

The speed of the mobile nodes is changed incrementally from the current speed $v(t')$ to the targeted new speed $v(t)$ by acceleration speed or deceleration speed $a(t)$ with a probability distribution function given by (2).

$$P(a) = \begin{cases} \dfrac{1}{a_{\max}} & acceleration: 0 < a \le a_{\max} \\ \dfrac{1}{a_{\min}} & deceleration: a_{\min} \le a \le 0 \\ 0 & otherwise \end{cases} \quad (2)$$

The movement direction of the sensor nodes is uniformly distributed in the interval $[0, 2\pi]$, with probability distribution given by (3).

$$P_\phi(\phi) = \frac{1}{2\pi}\, for: 0 \le \phi \le 2\pi \quad (3)$$

When the direction of a mobile node is about to change, the new movement direction is also selected according to the probability distribution function described by (3).

The node continues to move in the new direction with the given distribution. Future work will be to utilized data of elderly patients in assisted living communities to enhance this mobility model.

B. Simulation Stages

Monte Carlo analysis using full lifetime simulation is impractical due to the nature of the WSN nodes that can last for months at a time. An alternative is to split the simulation into two stages and rely on the power used by nodes being roughly constant in the steady state.

Stage 1 Simulation: In stage 1, each node is initialized with fully charged batteries (i.e. the energy is E_{max}). The output of the stage 1 simulation is the energy ΔE_i used by each node in a fixed time (T_e = 500s in this work). The simulation is run for time T_e to obtain the average power used by each node. The time is determined based on the average interval τ as Te = n τ (n =5 was used in this work). The average power used by each node is $P_i = \dfrac{\Delta E_i}{T_e}$.

Stage 2 Simulation: In stage 2, the powers obtained in stage 1 are used to determine when the first node fails. The second stage uses sequential approximation to reduce the running time as follows: The energy consumed by each node in stage 2 run is approximated by:

$$E_{consumed} = E_{\max}\left(\frac{P_i}{\max\{P\}}\right) \quad (5)$$

The starting energies of each node in stage 2 are, therefore

$$E_i = E_{\max}\left(1 - \frac{P_i}{\max\{P\}}\right) \quad (6)$$

The power consumed by a node in transmitting or receiving stimuli is within the range $0 \le P \le \max\{P\}$, therefore this approximation ensures that the node using maximum power has zero energy at the start of the next iteration. Monte Carlo method is performed using the starting energies in (6). The starting energies of each node before each simulation run are given by sequence:

Run 1:

$$E_i^0 = E_{\max}\left(1 - \frac{P_i}{\max\{P\}}\right) \quad (7)$$

Run 2:

$$E_i^1 = E^0\left(1 - \frac{P_i}{\max\{P\}}\right) \quad (8)$$

Run 3:

$$E_i^2 = E^1\left(1 - \frac{P_i}{\max\{P\}}\right) \quad (9)$$

Then the starting energy for the nth run would be

$$E_i^{n-1} = E\max\left(1 - \frac{P_i}{\max\{P\}}\right)\left(1 - \frac{P_i}{\max\{P\}}\right)\left(1 - \frac{P_i}{\max\{P\}}\right)\cdots\left(1 - \frac{P_i}{\max\{P\}}\right) \quad (10)$$

The runs form a geometrical distribution with expectation given by $1/p$ where p is the probability of first node failing. The probability of the first node failing after the stage 2 is given by

$$p \le E[P_i]\frac{T_e + T_{skip}}{E_{\max}} \quad (11)$$

Each simulation run M generates the number of working nodes N as a function of time t given by $N(t)$. The change in time for the nodes to reduce from maximum working nodes N to $N-1$ is given as the time for the first node to fail.

III. Results

A HMN with 23 bio-sensor nodes, a base station and two target or source nodes is simulated with the J-Sim network simulator. Each patient moves in a square grid of 200m by 200m. The motion of each patient is simulated with the Smooth Random Mobility model, which exhibits temporal dependence on velocity. Each sensor node is injected with the appropriate traffic rate - 8Kbits/s for the ECG sensor and 64bits/s for the pulse oximeter sensor. ECG assumes high traffic rate because of the detection of its numerous parameters (P-, T-, QRS-complexes, P-wave, R-wave, T-waves, and the cardiac intervals). The transport agent is the User Datagram Protocol UDP. The J-Sim free-space propagation is used as the radio communication model. The wireless physical layer parameters are adjusted according to those of the CodeBlue [1] platform, which utilizes the Chipcon [8] CC2420 radio interface. The initial energy of all nodes is 25200J; this value is chosen as a starting point. The simulator running time is 500s. The number of runs is different for each protocol.

A. Network Infrastructure Failure Analysis

This shows the Cumulative Distribution Functions (CDFs) of the time to lose a fraction of the working nodes for the various routing protocols. Fig. 1 shows the CDFs of the time to lose a fraction of the nodes for AODV protocol. The data for this distribution is separated by runs. The runs for 10%, 50% and 96% CDFs are shown, which is interpreted as the distribution of the time to lose 90%, 50%, and 4% of the nodes respectively. These distributions can be used to approximately calculate the time that it takes for the first node running AODV to fail. These calculations can be done as follows: Considering that the simulated network consisted of 23 nodes, the runs corresponding to the subplot (in Figure 1) that shows "96% of the nodes remaining" mean that $4/100 * 23 \approx 1$ node has failed. This is approximately 104 days considering the mean (50%) performance. The lifetime of the network running AODV is very short. The 50% and 90% CDFs in Fig. 1 are somewhat similar indicating that the number of nodes drops quickly once the nodes start to fail.

Fig. 2 shows similar CDFs for single-hop protocol. Using similar analysis for single-hop, the distribution of the time for the first node to fail can be found to be approximately 220 days considering the mean performance. Secondly the difference in time between the 50% and 90% CDFs in Fig. 2 are quite wide indicating the number of nodes drops slowly once the nodes starts to fail. Similar results were obtained for Multi-hop protocol in Fig. 3. The distribution of the time for the first node to fail to fail was centered around 300 days considering the mean performance. The lifetime of the Multi-hop protocol is very long. Also the number of nodes drops quite slowly once the nodes start to fail.

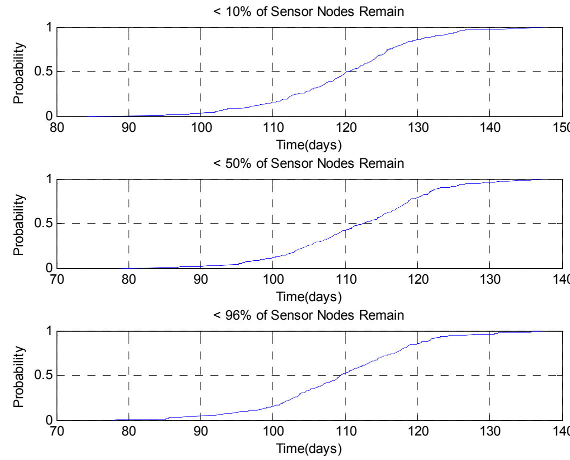

Fig. 1: Distributions of time required to be left with 96%, 50%, and 10% working nodes for a network using AODV protocol

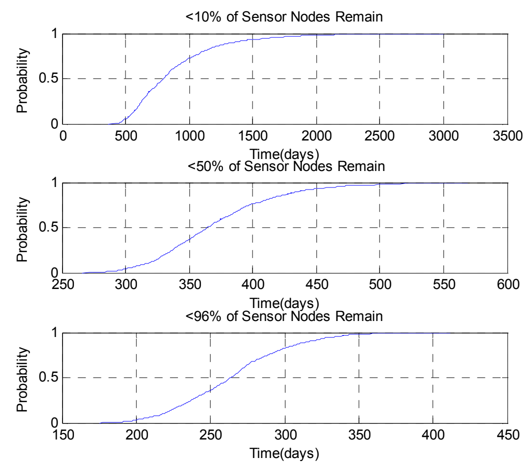

Fig. 2: Distributions of time required to be left with 96%, 50%, and 10% working nodes for a network using single-hop protocol

B. Network Lifetime

This shows the lifetime of the nodes running various routing protocols represented as mean time and standard deviation in days. Fig. 4, 5 and 6 show the lifetime of the nodes running the AODV, single-hop and multi-hop protocols respectively. The mean time for the first node running AODV to fail is approximately 100 days with a standard deviation of 13 days. The mean time for first node running single-hop protocol to fail is 190 days with a standard deviation of 30 days. Similarly it takes 339 days for the first node running multi-hop to fail with a standard deviation of 84 days.

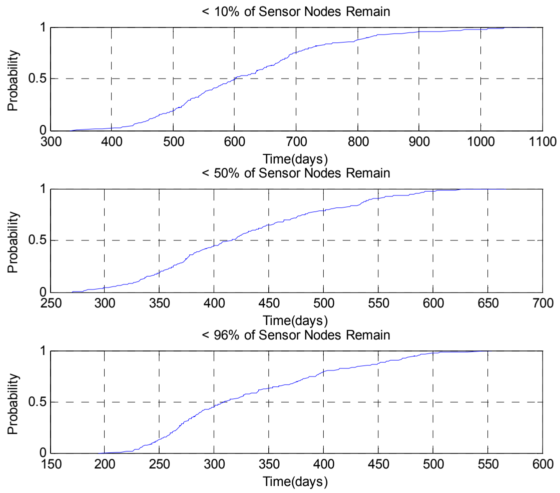

Fig. 3: Distributions of time required to be left with 96%, 50%, and 10% working nodes for a network using multi-hop protocol

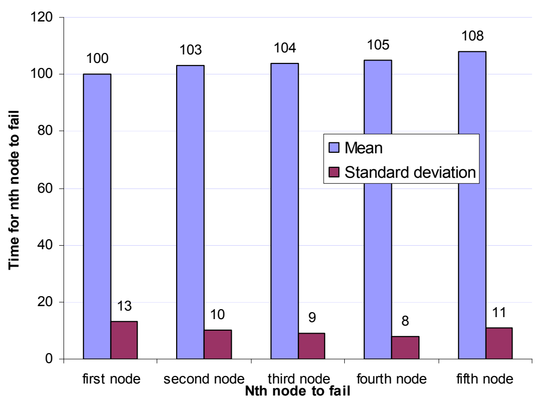

Fig. 4: Mean Lifetime (in days) of nodes for the HMN running AODV

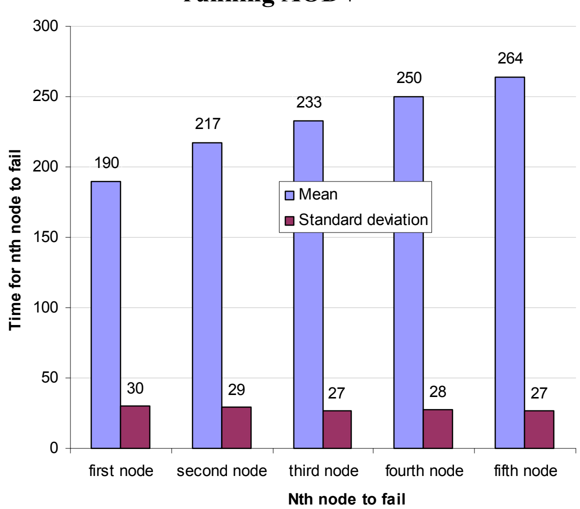

Fig. 5: Mean Lifetime (in days) of nodes for the HMN running Single-hop

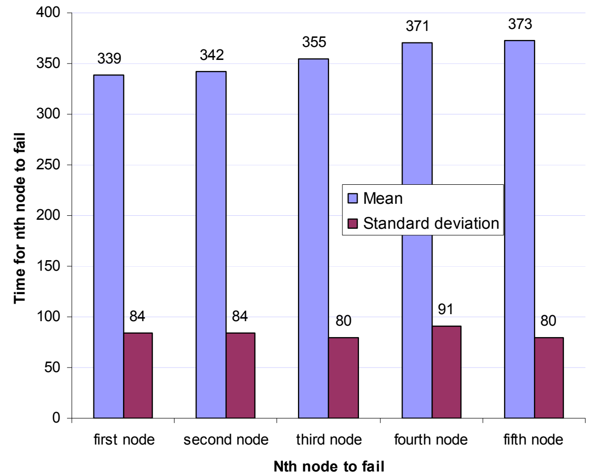

Fig. 6: Mean Lifetime (in days) of nodes for the HMN running Multi-hop

IV. CONCLUSIONS

The model described effectively estimate the lifetime of the WBASN by incorporating probabilistic behavior. The lifetime for the AODV protocol is short and this is due to the complexity of the routing protocol in sending route request (RREQ) and route reply (RREP) messages. The lifetime for the Multi-hop protocol is quite long due to the simplicity of the protocol but a standard deviation of 84 days is too wide for this protocol to be a good choice for WBASN.

In future work, the distributions of the monitored signals (ECG, SpO2) will be improved to capture realistic scenarios such as "false alarms", that is, when the blood pressure or ECG of a patient rises simply because the patient is walking up the stairs. Additionally, new protocols will be incorporated and evaluated to determine their suitability for use in a HMN.

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