Modeling and Analysis of Energy Harvesting Nodes in Body Sensor Networks

Alireza Seyedi
Department of Electrical and Computer Engineering
University of Rochester
Email: alireza.seyedi@ieee.org

Biplab Sikdar
Electrical, Computers and Systems Engineering Department
Rensselaer Polytechnic Institute
Email: bsikdar@ecse.rpi.edu

***Abstract*—A Markov based unified model for an energy harvesting node in a body sensor network is presented. Using the presented model, the probability of event loss due to energy run out is calculated. The results provide insight into the performance of energy harvesting nodes in a body sensor network as well as design requirements for such devices.**

I. Introduction

Body Sensor Networks (BSNs) [1] are envisioned to revolutionize many fields such as health monitoring and personal health care. By connecting multiple real time sensors and actuators to each other and to off-body communication networks, these systems enable constant monitoring and data collection as well as interaction with the human body. This capability significantly advances many medical as well as non medical applications and services [2]-[9].

The energy supply for the sensor nodes is one of the major hurdles in the development and widespread deployment of BSN technology [10]. The current state-of-the-art battery technology does not provide sufficient energy density to allow the implementation of body sensor nodes with acceptable lifetime, cost, and form factor. The short lifetime of batteries with reasonable cost and form factor means that they must be replaced frequently. This is not only an inconvenience for the user, but also, it reduces the reliability of the BSNs. Moreover, for many applications where an *in vivo* (implanted) BSN node is used, replacing the batteries is not an option.

The most promising approach to address the energy supply problem for BSNs is energy harvesting (or energy scavenging) [1][11]-[13]. In this approach the sensors are equipped with an energy harvesting device that collects energy from ambient sources such as motion, light, and heat. Energy harvesting expands the design space of communication systems into a new dimension. In presence of energy harvesting, the energy supply of a sensor node can no longer be described with simple, deterministic models. Traditionally, either it is assumed that the energy supply is unlimited, or that the energy supply is monotonically decreasing with a fixed initial value. Since energy harvesting sensors can replenish their supply of energy, they require a much more sophisticated energy model. Thus, in addition to the previously considered factors such as channel models and traffic models, *energy models* must also be considered as an essential factor in the design of communication systems.

In this paper we will provide a unified model that combines the energy model and the traffic model. Using this model which describes the state of the system by including both the harvesting state as well as the remaining energy supply of the device, we provide an analysis of the probability of event loss due to energy run out.

II. System Model

In this section we will provide a discrete time model that integrates the energy model and the traffic model. This model allows us to analyze the overall system and obtain performance metrics. These performance metrics will in turn tell us about the reliability of the system and give us guidance regarding the design requirements.

A. Energy Model

We assume that motion based energy harvesting is used, and model the energy harvesting process with a two state Markov chain. That is, we assume that the subject is in one of the two activity states, namely *walk* and *rest*. We assume that at the end of each time slot the subject will go from *walk* to *rest* with probability r, and from *rest* to *walk* with probability w. Consequently, the probabilities that the subject stays in the *walk* or *rest* states are $1-r$ and $1-w$, respectively. Furthermore, we assume that the energy harvesting device will harvest energy with an average rate (power) of ρ_w when in the *walk* state and does not harvest any energy when in the *rest* state.

Given this model, the average number of time slots that the subject stays in the *walk* state is given by

$$\sum_{k=1}^{\infty} k(1-r)^{k-1} r = \frac{1}{r}. \tag{1}$$

Similarly, the average number of time slots that the subject stays in the *rest* state is given by $\frac{1}{w}$. Moreover, it can easily be shown that the steady state probability that the subject is in the *walk* and *rest* states are $\mu_w = \frac{w}{r+w}$ and $\mu_r = \frac{r}{r+w}$, respectively. Therefore, the average expected harvested power will be given by $\rho = \frac{w}{r+w}\rho_w$.

B. Traffic Model

We consider a simple traffic model. That is, we assume that in each time slot, an event occurs with probability p.

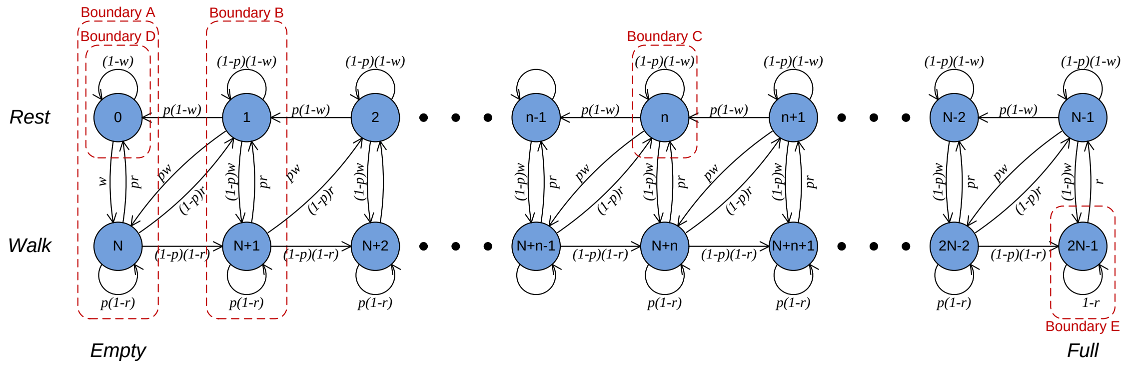

Fig. 1. Markov chain model combining energy model and traffic models.

Furthermore, we assume that each event has a total energy cost of E_0, which includes the energy consumed by the sensor or actuator, the energy consumed for signal processing and the energy consumed for the transmission or reception of the related data.

C. Overall System Model

To combine the energy and traffic models described above, we consider the time unit to be equal to the length of the time required to harvest enough energy for one event, given that the subject is in the *walk* state. That is, we define the time unit to be $T = E_0/\rho_w$. Moreover, we assume that the total battery capacity for the device is equal to $B = NE_0$.

With this definition of the time unit, we can consider four different cases for each time slot:

- The subject is in the *rest* state and an event occurs. In this case, the energy level in the device will decrease by E_0, unless the device has already ran out of energy.
- The subject is in the *rest* state and an event does not occur. In this case, the energy level in the device will not change.
- The subject is in the *walk* state and an event occurs. In this case, the energy level in the device will not change.
- The subject is in the *walk* state and an event does not occur. In this case, the energy level in the device will increase by E_0, unless it has reached its maximum, B (*i.e.* the battery is full).

We can then model the state of the device using a $2N$ state Markov chain. The state of the device will represent its energy harvesting state (*i.e.* *walk* or *rest*) as well as the amount of energy stored in the battery. Such a Markov chain is depicted in Figure 1. In this model, states 0 through $N-1$ represent the case where the subject is in the *rest* state. The subject is in the *walk* state if the system is in states N through $2N-1$. Furthermore, the amount of energy stored in the battery is given by $E = (n \bmod N)E_0$, where n is the state number. In other words, the battery is empty in states 0 and N, and is completely full in states $N-1$ and $2N-1$.

The components of the transition matrix $\mathbf{P}$ for this Markov chain are given by

$$P_{0,j} = \begin{cases} 1-w & j=0 \\ w & j=N \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

and

$$P_{2N-1,j} = \begin{cases} 1-r & j=2N-1 \\ r & j=N-1 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

for states 0 and $2N-1$, and

$$P_{i,j} = \begin{cases} (1-p)(1-w) & j=i \\ p(1-w) & j=i-1 \\ (1-p)w & j=i+N \\ pw & j=i+N-1 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

and

$$P_{i,j} = \begin{cases} p(1-r) & j=i \\ (1-p)(1-r) & j=i+1 \\ pr & j=i-N \\ (1-p)r & j=i-N+1 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

for other states.

III. System Analysis

We are interested in finding the average probability that an event is lost (*i.e.* is not sensed and reported), due to lack of sufficient energy in the device. To find this probability, we note that an event is lost if and only if the event occurs when the device is in state 0. Note that when the device is in state N it will collect sufficient energy during one time slot for the event. When the device is in all other states, it has sufficient energy stored in its battery. Therefore, we can write the probability of event loss by

$$p_L = \pi_0 \tag{6}$$

where π_n denotes the steady state probability that the Markov chain is in state n. Note that since this Markov chain is of finite length, irreducible and non periodic, it has a steady state.

The steady state probabilities for all states can be obtained using the eigen analysis of the transition matrix, $\mathbf{P}$. That is, if the eigen decomposition of the transition matrix is given by

$$\mathbf{P} = \mathbf{V}^{\dagger}\mathbf{\Lambda}\mathbf{V} \tag{7}$$

then the columns of $\mathbf{V}$, $\mathbf{v_k}, k = 0, ..., 2N-1$, are the eigen vectors of $\mathbf{P}$ and the components of the diagonal matrix $\mathbf{\Lambda}$, $\lambda_k, k = 0, ..., 2N-1$, are its eigen values. Then the steady state probabilities $\boldsymbol{\pi} = [\pi_0, ..., \pi_{2N-1}]^T$ will be given by the eigen vector corresponding to an eigen value of unity. That is,$\boldsymbol{\pi} = \mathbf{v}_{k_0}$, where $\lambda_{k_0} = 1$.

While this method provides a general solution for the steady state probabilities, the computation of eigen analysis of the matrix $\mathbf{P}$ quickly grows with N. The particular structure of this Markov chain, however, allows us to derive a closed form solution for the steady state probability π_0. To solve for $\boldsymbol{\pi}$, we write the equilibrium equations for different combination of states.

Considering a boundary containing the states 0 and N (Figure 1, Boundary A), the equilibrium equation is

$$pw\pi_1 + p(1-w)\pi_1 - (1-p)(1-r)\pi_N - (1-p)r\pi_N = 0 \quad (8)$$

or

$$p\pi_1 = (1-p)\pi_N. \quad (9)$$

Also, the equilibrium equation for a boundary around states 1 and $N+1$ (Figure 1, Boundary B) results in

$$p\pi_2 + (1-p)\pi_N - p\pi_1 - (1-p)\pi_{N+1} = 0. \quad (10)$$

Substituting (9) in (10) gives

$$p\pi_2 = (1-p)\pi_{N+1}. \quad (11)$$

By continuing this procedure for states n and $N+n$ for $n = 1, ..., N-1$, we can conclude that

$$\pi_n = a\pi_{N+n-1} \quad (12)$$

where

$$a = \frac{1-p}{p}. \quad (13)$$

The equilibrium equation for a boundary around state n, where $1 \le n \le N-2$ (Figure 1, Boundary C) results in

$$[p(1-w) + pw + (1-p)w]\pi_n - p(1-w)\pi_{n+1} - pr\pi_{N+n} - (1-p)r\pi_{N+n-1} = 0 \quad (14)$$

By substituting (12) in (14) we get

$$[p + (1-p)w - pr]\,\pi_n - [(1-p)(1-w) + pr]\pi_{N+n} = 0 \quad (15)$$

or

$$\pi_{N+n} = b\pi_n \quad (16)$$

where

$$b = \frac{p + (1-p)w - pr}{(1-p)(1-w) + pr}. \quad (17)$$

Also, the equilibrium equation for a boundary around state 0 (Figure 1, Boundary D) results in

$$w\pi_0 - pr\pi_N + p(1-w)\pi_1 = 0 \quad (18)$$

which using (9) becomes

$$w\pi_0 - [pr + (1-p)(1-w)]\,\pi_N = 0 \quad (19)$$

or

$$\pi_N = c\pi_0 \quad (20)$$

where

$$c = \frac{w}{pr + (1-p)(1-w)}. \quad (21)$$

Finally, the equilibrium equations for a boundary around state $2N-1$ (Figure 1, Boundary E) result in

$$r\pi_{2N-1} - (1-p)(1-r)\pi_{2N-2} - (1-p)w\pi_{N-1} = 0 \quad (22)$$

which using (9) becomes

$$r\pi_{2N-1} = [p(1-r) + (1-p)w]\,\pi_{N-1} \quad (23)$$

or

$$\pi_{2N-1} = d\pi_{N-1} \quad (24)$$

where

$$d = \frac{p(1-r) + (1-p)w}{r}. \quad (25)$$

By combining (12), (16), (20), and (24), we can have

$$\pi_n = a^n b^{n-1} c\pi_0 \quad (26)$$

and

$$\pi_{N+n-1} = a^{n-1} b^{n-1} c\pi_0 \quad (27)$$

for $1 \le n \le N-1$, and

$$\pi_{2N-1} = a^{N-1} b^{N-2} cd\pi_0. \quad (28)$$

Now we apply the constraint

$$\sum_{n=0}^{2N-1} \pi_n = 1, \quad (29)$$

or

$$\pi_0 + \sum_{n=1}^{N-1} a^n b^{n-1} c\pi_0 + \sum_{n=1}^{N-1} a^{n-1} b^{n-1} c\pi_0 + da^{N-1} b^{N-2} c\pi_0 = 1 \quad (30)$$

which yields

$$\pi_0 = \frac{1}{1 + c(a+1)\frac{1-a^{N-1}b^{N-1}}{1-ab} + da^{N-1}b^{N-2}c}. \quad (31)$$

IV. Results

Figure 2 compares the probability of event loss obtained from theory (Equations (6) and (31)) and those obtained from Monte Carlo simulations. We have assumed that $w = 0.005$ and $r = 0.045$, which means that the subject is in the *walk* state 10% of the time and in the *rest* state for 90% of the time. Moreover, we have assumed that $N = 20$. We observe that the simulation results and the theoretical results match very closely.

Figure 3 presents the event loss probability versus normalized battery capacity, $N = B/E_0$. Once again we have assumed that $w = 0.005$ and $r = 0.045$. We can see that as expected larger battery capacities lead to significant drop in the event loss probability. We observe that to achieve event loss probability of 10^{-5} or better, we would require a battery size of $B \ge 32E_0$ and $B \ge 99E_0$ for $p = 0.01$ and $p = 0.03$, respectively. Even battery sizes as large as

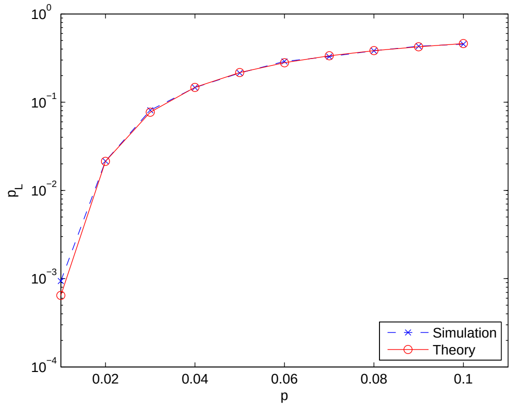

Fig. 2. Comparison between theoretical and simulated probability of event loss.

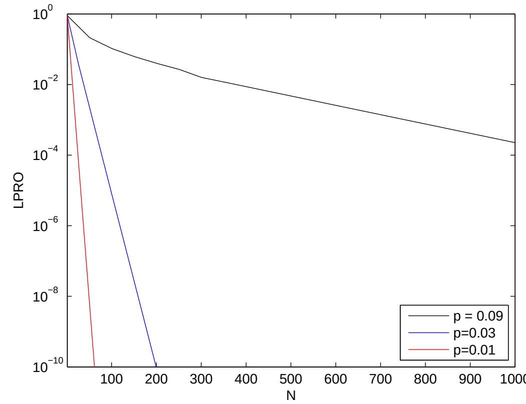

Fig. 3. Probability of event loss as a function of battery size.

$B \geq 1000E_0$, however, will not be sufficient to reduce the event loss probability near 10^{-5}.

Figure 4 depicts the probability of event loss as a function of w and $w/(r + w)$. Here we have assumed that $p = 0.01$ and $N = 20$. Note that $w/(r + w)$ represents the average portion of the time the subject is in the *walk* state. Also, for a given $w/(r+w)$, the value of w will determine the average frequency that the subject moves between *rest* and *walk* states. We observe that spending a large percentage of the time in the *walk* state alone is not sufficient to achieve low event loss probability, if the *rest/walk* cycles are long. This is because a long *rest* period will eventually consume the energy stored in the battery and result in many event losses. Hence, we can see that that to achieve low event loss probability, large values of both w and $w/(r + w)$ are needed.

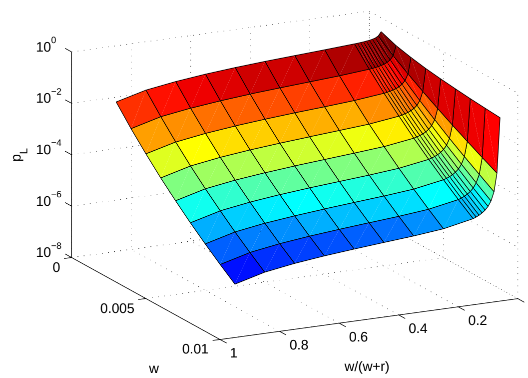

Fig. 4. Probability of event loss as a function of average event rate and average *walk* time.

V. CONCLUSIONS

In this paper we have presented a Markov based model for energy harvesting nodes in body sensor networks. The presented model considers both the state of the energy harvesting process as well as the remaining energy supply of the node to determine the state of the node. A closed form solution for the event loss probability is then derived from the presented models. The results provide insight into the relationship between system parameters such as average harvested power and average traffic rate and maximum battery capacity and give us guidance to set the requirements for energy harvesting nodes in a body sensor network.

REFERENCES

[1] G. Z. Yang, *Body Sensor Networks,* Springer, London, 2006.

[2] O. Aziz, B. Lo, R. King, A. Darzi and G.-Z. Yang, "Pervasive body sensor network: an approach to monitoring the post-operative surgical patient," *Proceedings of International Workshop on Wearable and Implantable Body Sensor Networks,* Apr. 2006.

[3] T. Falck, J. Espina, J. P. Ebert and D. Dietterle, "BASUMA - the sixth sense for chronically ill patients," *Proceedings of International Workshop on Wearable and Implantable Body Sensor Networks,* Apr. 2006.

[4] E. Jovanov, A. O'Donnell Lords, D. Raskovic, P. G. Cox, R. Adhami and F. Andrasik, "Stress monitoring using a distributed wireless intelligent sensor system," *IEEE Engineering in Medicine and Biology Magazine,* vol. 22, no. 3, pp. 49-55, May-Jun 2003.

[5] S. Patel, D. Sherrill, R. Hughes, T. Hester, N. Huggins, T. Lie-Nemeth, D. Standaert and P. Bonato, "Analysis of the severity of dyskinesia in patients with Parkinson's disease via wearable sensors," *Proceedings of International Workshop on Wearable and Implantable Body Sensor Networks,* Apr. 2006.

[6] S. D. Bao, Y. T. Zhang and L. F. Shen, "Physiological Signal Based Entity Authentication for Body Area Sensor Networks and Mobile Healthcare Systems," *Proceedings of the 27th Annual International Conference of the Engineering in Medicine and Biology Society,* pp. 2455-2458, 2005.

[7] G. Bordello, W. Brunette, J. Lester, P. Powledge and A. Rea, "An ecosystem of platforms to support sensors for personal fitness," *Proceedings of International Workshop on Wearable and Implantable Body Sensor Networks,* Apr. 2006.

[8] A. Krause, A. Smailagic and D. P. Siewiorek, "Context-aware mobile computing: learning context- dependent personal preferences from a wearable sensor array," *IEEE Transactions on Mobile Computing,* vol. 5, no. 2, pp. 113-127, Feb. 2006.

[9] J. A. Ward, P. Lukowicz, G. Troster and T. E. Starner, "Activity Recognition of Assembly Tasks Using Body-Worn Microphones and Accelerometers," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 28, no. 10, pp. 1553-1567, Oct. 2006.

[10] L. Schwiebert, S. K. S. Gupta and J. Weinmann, "Research Challenges in Wireless Networks of Biomedical Sensors," *Proceedings of The Seventh Annual International Conference on Mobile Computing and Networking,* pp. 151-165, Jul. 2001.

[11] J. A. Paradiso and T. Starner, "Energy scavenging for mobile and wireless electronics," *IEEE Pervasive Computing,* vol. 4, no. 1, pp. 18-27, January-March 2005.

[12] E. K. Reilly and P. K. Wright, "Energy Scavenging for Body Sensor Networks," *Proceedings of ACM BodyNets'07,* June 2007.

[13] N. S. Shenck and J. A. Paradiso, "Energy Scavenging with Shoe-Mounted Piezoelectrics," *IEEE Micro,* vol. 21, no.. 3, pp. 30-42, 2001.