Energy Consumption Model for Data Processing and Transmission in Energy Harvesting Wireless Sensors

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Abstract. This paper studies energy harvesting wireless sensor nodes in which energy is gathered through harvesting process and data is gathered through sensing from the environment at random rates. These packets can be stored in node buffers as discrete packet forms which were previously introduced in "Energy Packet Network" paradigm. We consider a standby energy loss in the energy buffer (battery or capacitor) in a random rate, due to the fact that energy storages have self discharge characteristic. The wireless sensor node consumes K_e and K_t amount of harvested energy for node electronics (data sensing and processing operations) and wireless data transmission, respectively. Therefore, whenever a sensor node has less than K_e amount of energy, data can not be sensed and stored, and whenever there is more than K_e amount of energy, data is sensed and stored and also it could be transmitted immediately if the remaining energy is greater or equal than the K_t . We assume that the values of both K_e and K_t as one energy packet, which leads us a one-dimensional random walk modeling for the transmission system. We obtain stationary probability distribution as a product form solution and study on other quantities of interests. We also study on transmission errors among a set of M identical sensor with the presence of interference and noise.

Keywords: Wireless sensors \cdot Energy harvesting \cdot Energy packets \cdot Data packets \cdot Standby energy loss \cdot Energy leakage \cdot Data leakage \cdot Markov modeling

1 Introduction

DOI: 10.1007/978-3-319-47217-1_13

Wireless sensor network (WSN) is an essential part of IoT, which is composed of several sensors to sense physical data from the environment. The sensed data may be processed, stored, and transmitted by the sensor and communicate with a user or observer via Internet. A WSN can be used in many different areas such as [1]: health monitoring [2], environmental and earth sensing [3], industrial monitoring [4], and military applications [5]. Several application areas increase the usage of © The Author(s) 2016 T. Czachórski et al. (Eds.): ISCIS 2016, CCIS 659, pp. 117–125, 2016. WSN numerously. While the worldwide number of the wireless-sensing points available is 4 million in 2011, more than 25 million available wireless-sensing points would be expected by 2017 [6], so that the envisaged market rise of WSN is from \$0.5 billion in 2012 to \$2 billion in 2022 [7].

When all energy is consumed in a sensor, it can not operate properly and can not achieve its role unless a new energy source is provided. However, replacing batteries or maintaining line connection for WSN usage is not convenient, so that the finite energy sources is a major constraint of WSNs. This has pushed to find an alternative energy source for WSNs, so that harvesting ambient energy from the environment has been addressed this problem and it has particular importance among these systems.

Earlier works [8,9] studied the performance of an energy harvesting sensor node as a function of random data and energy flow. Moreover, in [10,11] performance analysis was improved by taking into account the energy leakage from the storage due to standby operation, and [12] studied the case where exactly Kenergy packets are needed for successful transmission of 1 data packet. In earlier works, one of the main assumptions is that energy is only consumed for the packet transmission, not packet sensing and processing operations in the node. In this paper, the main contribution is that we consider energy consumption not only for data transmission but also for node electronics, i.e., data sensingprocessing-stroring in an energy harvesting wireless sensor. The quantities of interest such as stationary probability distributions, excessive packet rates, and backlog probabilities for stability analysis is obtained. We also consider the transmission errors for the system and study on relation between system parameters and error probabilities.

2 Mathematical Model

We model a wireless sensor node where data and energy is received randomly from the environment. The arrivals of data packets and energy packets to the node are assumed to be independent Poisson process with rates λ and Λ , respectively. The term "energy packet" is a paradigm where energy is assumed to be in a discrete form. The sensor node contains a data buffer and an energy storage (capacitor or battery) to store receiving packets. Due to self discharge nature of energy storages, there is a standby loss in the system, that can be modeled as another independent Poisson process with rate μ . The sensing and the transmission occurs very fast at the node compared to the data and energy gathering rates from the environment, so that the operation times required for sensing and transmission processes are negligible, i.e., they occur instantaneously. In a sensor node, the harvested energy is basically consumed for packet sensing, storing, processing and transmission. In our system, we assume that $K_e = 1$ energy packet is required for the node electronics (sensing, storing, processing) and $K_t = 1$ energy packet is required for the data transmission, so that total two energy packets are needed for transmitting one data packet. Therefore, whenever a sensor node has less than Ke = 1 energy packet, data can not be sensed and



Fig. 1. State diagram representation of the system

stored, and whenever there is more than Ke amount of energy packet, data is sensed and stored and also it could be transmitted immediately if the remaining energy is greater or equal than the Kt = 1 energy packet.

Consider the system at a time $t \ge 0$ contains amount of D(t) data packets in the buffer and amount of E(t) energy packets in the storage, so that we can model the state of sensor node by the pair of (D(t), E(t)). Whenever $E(t) \ge 1$, node can sense the data packet and one energy packet is consumed by the node electronics instantaneously. Also, if there is still available energy in the storage, node can also transmit the data packet by consuming one more energy packet immediately.

When we examine the system model carefully, since the model has a finite state space, an unbounded growth of data or energy packets is not allowed. In fact, when one data packet arrives to the node whose state is (D(t) = 0, E(t) = 1), the state will change as (D(t) = 1, E(t) = 0) and it is the only state where data buffer is not empty. This interesting situation leads the system has great amount of excessive data packets, which we will consider later.

Let us write p(d, e, t) = Prob[D(t) = d, E(t) = e]. By using above remark, we should only consider p(d, e, t) for the state space S such that $(e - d) \in S$, where $E \ge (e - d) \ge -1$ and E is the maximum amount of energy packets that can be stored in the node.

In fact, the system can be modeled as finite Markov chain whose states and transition diagram can be seen in Fig. 1. The stationary probabilities $p(e-d) = \lim_{t\to\infty} Prob[D(t) = d, E(t) = e]$ can be computed from following balance equations:

$$p(-1)[\Lambda] = \lambda \ p(1) \tag{1}$$

$$p(0)[\Lambda] = \Lambda \ p(-1) + \lambda \ p(2) + \mu \ p(1)$$
(2)

$$p(N)[\Lambda + \lambda + \mu] = \Lambda p(N-1) + \lambda p(N+2) + \mu p(N+1)$$
(3)

$$p(E-1)[\Lambda + \lambda + \mu] = \Lambda \ p(E-2) + \mu \ p(E) \tag{4}$$

$$p(E)[\lambda + \mu] = \Lambda \ p(E - 1). \tag{5}$$

Note that (3) is valid for 0 < N < E - 1 and has a solution of the form:

$$p(N) = c \varphi^N \tag{6}$$

where c is an arbitrary constant and φ can be computed from following characteristic equation:

$$\lambda \varphi^3 + \mu \varphi^2 - (\Lambda + \lambda + \mu)\varphi + \Lambda = 0 \tag{7}$$

whose roots are $\{\varphi_1 = 1, \varphi_{2,3} = \frac{-(\lambda+\mu)\mp\sqrt{(\lambda+\mu)^2+4\Lambda\lambda}}{2\lambda}$. Here only viable root is φ_3 , since the solution must lie in the interval (0,1). In the rest of the paper, we consider $\varphi_3 = \varphi$ for the sake of simplicity.

After finding stationary probabilities of the states between the interval (0, E-1), we may also reach:

$$\begin{split} p(-1) &= c\frac{\lambda}{\Lambda}\varphi, \ \ p(0) = c(\frac{\lambda}{\Lambda}\varphi^2 + \frac{\lambda+\mu}{\Lambda}\varphi), \\ p(E-1) &= c[1 + \frac{\lambda+\mu}{\Lambda} - \frac{\mu}{\lambda+\mu}]^{-1}\varphi^{E-2}, \\ p(E) &= c[(\frac{\lambda+\mu}{\Lambda})(\frac{\Lambda+\lambda+\mu}{\Lambda}) - \frac{\mu}{\Lambda}]^{-1}\varphi^{E-2}. \end{split}$$

Using the fact that summation of the probabilities is one:

$$\sum_{N=-1}^{E} p(N) = c(\frac{2\lambda+\mu}{\Lambda}\varphi + \frac{\lambda}{\Lambda}\varphi^2) + c\sum_{N=1}^{E-2} \varphi^N + c[\frac{\lambda+\mu}{\Lambda} - \frac{\mu}{\Lambda+\lambda+\mu}]^{-1}\varphi^{E-2} = 1.$$

After further calculations, we may reach:

$$c = [\frac{2\lambda + \mu}{\Lambda}\varphi + \frac{\lambda}{\Lambda}\varphi^2 + \frac{\varphi - \varphi^{E-1}}{1 - \varphi} + \frac{\Lambda(\Lambda + \lambda + \mu)}{(\lambda + \mu)(\Lambda + \lambda + \mu) - \mu\Lambda}\varphi^{E-2}]^{-1}.$$

2.1 Excessive Packets Due to Finite Buffer Sizes

Since the energy storage capacity (maximum E energy packets) and data buffer capacity (maximum B data packets) are finite and data buffer is forced to be empty most of the time, we have some excessive packets that arrive at the node, but can not be sensed and stored. These excessive packets rates, Γ_d and Γ_e for data and energy packets, respectively and can be computed as:

$$\begin{split} \Gamma_d &= \lambda \sum_{N=0}^{-B} p(N) = \lambda(p(0) + p(-1)) = c\lambda(\frac{2\lambda + \mu}{\Lambda}\varphi + \frac{\lambda}{\Lambda}\varphi^2),\\ \Gamma_e &= \Lambda p(E) = c[\frac{1}{\Lambda}[(\frac{\lambda + \mu}{\Lambda})(\frac{\Lambda + \lambda + \mu}{\Lambda}) - \frac{\mu}{\Lambda}]]^{-1}\varphi^{E-2}. \end{split}$$

Obviously, increase in the arrival rates of the energy and the data packets will increase the excessive packet rates. We can observe Γ_d remains zero until a certain level of λ and after this level, it starts showing a decreasingly growing behavior in Fig. 2, where we assume $\Lambda = 10, \mu = 1, E = 100$ for several values of λ . Although the system does not allow to store more than one data packet in the buffer, we observe reasonable amount of excessive data packet rate, which is due to the fact that most of the data packets can be sensed and transmitted when there are two or more energy packets in the node.

In Fig. 2, we may also observe similar effect on Γ_e where we assume $\lambda = 10, \mu = 0.1\Lambda, E = 100$ for several values of Λ . Apart from the previous observation, increase in Γ_e is nearly linear after a certain level of Λ .



Fig. 2. Excessive data and energy packet rates.

2.2 Stability of the System

System stability is the question of whether finite number of segregated data packets and energy packets remain finite with certain probability for unlimited data and energy storage capacity when $t \to \infty$. If the condition is satisfied, then the system will be said to be stable.

Here, in order to make further analysis, we need to re-consider system with unlimited storages. In this case, we may reach:

$$p(-1) = c' \frac{\lambda}{\Lambda} \varphi, \ p(0) = c' (\frac{\lambda}{\Lambda} \varphi^2 + \frac{\lambda + \mu}{\Lambda} \varphi), \ p(N) = c' \varphi^N, \ 0 < N < \infty.$$

where φ is the same with the one solution of 7 and c' value can be computed as:

$$c' = \frac{(\lambda + \mu - 2\Lambda) + \sqrt{(\lambda + \mu)^2 + 4\Lambda\lambda}}{2(2\lambda + \mu)}.$$

Also, we can express the marginal probabilities as:

$$p_d(d) = \sum_{e=0}^{\infty} p(e-d)$$
 and $p_e(e) = \sum_{d=0}^{\infty} p(e-d)$.

In steady state, the probabilities that segregated data packets and energy packets do not exceed some finite values D' and E', respectively:

$$P_d(D') = \lim_{t \to \infty} Prob[0 < D(t) \le D' < \infty], \tag{8}$$

$$P_e(E') = \lim_{t \to \infty} Prob[0 < E(t) \le E' < \infty].$$
(9)

We can calculate 8 and 9 by using marginal probabilities:

$$P_d(D') = \sum_{d=0}^{D'} \sum_{e=0}^{\infty} p(e-d) = p_d(1) + p_d(0) = p(-1) + p(0) + \sum_{N=1}^{\infty} c' \varphi^N = 1.$$

and

$$P_e(E') = \sum_{e=0}^{E'} \sum_{d=0}^{\infty} p(e-d) = p_e(0) + p_e(e)\mathbf{1}[e>0] = p(-1) + p(0) + \sum_{N=1}^{E'} c'\varphi^N$$
$$= 1 - c'\frac{\varphi^{E'+1}}{1-\varphi}.$$

Thus, we can conclude that the system with unlimited storage capacities is always stable with respect to data packets and unstable with respect to energy packets, as expected.

3 Analysis of Transmission Error Among a Set of Nodes

The total power that is entering the sensor node is simply energy harvesting rate Λ , due to the fact that energy rate is in unit of power. All harvested power can not be used by the node, since there are some energy packet losses, namely standby loss due to the self-discharge nature of the storage and excessive packet loss due to limited capacity storage of the node, so that the total power consumed by the node is:

$$\xi_{i} = \Lambda_{i} - \Gamma_{e_{i}} - \mu_{i} \sum_{N=1}^{E} p_{i}(N), \qquad (10)$$

where the subscript *i* relates to the parameters of the *i*-th node among the set of M nodes. Whenever a node transmits a data packet, it consumes amount of K_e and K_t energy packets for node electronics and packet transmission, respectively. Since it is assumed that $K_e = K_t$, the total radiating power from a sensor on average is simply:

$$\phi_i = \frac{\xi_i}{2}.\tag{11}$$

Furthermore, if the probability of correctly receiving (or decoding) the packet sent by a given node i that transmits at power level K_{t_i} be denoted by:

$$1 - e_i = f(\frac{\eta_i K_{t_i}}{I_i + B_i}),\tag{12}$$

where f is some increasing function of its argument which is the signal to interference I_i plus noise B_i and $0 \le \eta_i \le 1$ represents the propagation factor of the transmission power that is sensed by the receiver.

Some number of ' α ' separate frequency channels may be used in the communication medium. If the number of transmitting sensor nodes does not exceed α , distinct frequency channels are being used by each transmitter. In this case, interference can be considered as $I_{i_1} = \eta_i \kappa_{0_i} (M-1) \frac{\xi_i}{2}$, where $0 \le \kappa_{0_i} \le 1$ is a factor that represents the effect of side-band frequency channels and its value



Fig. 3. Transmission error probability vs number of sensor nodes

is expected to be very small. On the other hand, if the number of transmitting sensor nodes exceeds α , some of the transmitters is forced to use a frequency channel already used by others, so that it will cause an additional interference $I_{i_2} = \kappa_i \frac{M-\alpha}{M} \mathbb{1}[M > \alpha]$, where κ_i is very close to 1 since interference is direct to the channel. Thus the total interference is:

$$I_{i} = I_{i_{1}} + I_{i_{2}} = \eta_{i} \frac{\xi_{i}}{2} \kappa_{0_{i}} (M-1) + \eta_{i} \frac{\xi_{i}}{2} (\frac{M-\alpha}{M}) \mathbb{1}[M > \alpha].$$
(13)

If we assume that all nodes are identical, we can replace (12) by:

$$1 - e = f(\frac{\eta K_t}{\eta \frac{\xi}{2} \kappa_0 (M - 1) + \eta \frac{\xi}{2} (\frac{M - \alpha}{M}) \mathbf{1}[M > \alpha] + B}).$$
 (14)

Obviously, transmission error will raise with increase in number of sensor nodes in the network due to greater effect of the interference over the transmission. On the other hand, after a certain number of sensor nodes, α the system will face an additional interference, I_2 so that the error values will get higher values. We observe these effects in Fig. 3, where we assume that single bit transmission with $\Lambda = 10, \lambda = 10, \mu = 1, E = 100, B = 0.1, \eta = 0.5, \kappa_0 = 0.05, \alpha = 20$ and several values of M. Also, we assume BPSK transmission, so that:

$$1 - e = Q(\sqrt{\frac{\eta K_t}{\eta \frac{\xi}{2} \kappa_0 (M - 1) + \eta \frac{\xi}{2} (\frac{M - \alpha}{M}) \mathbb{1}[M > \alpha] + B}}),$$
(15)

where $Q(x) = \frac{1}{2} [1 - erf(\frac{x}{\sqrt{2}})].$

4 Conclusions

This paper analyses wireless sensor nodes that gather both data and energy from the environment in random manners, so that they are able to operate autonomously. The energy consumption in a node is divided in two operations: for the data transmission K_t , and for the node electronics (sensing and processing) K_e that is the main novelty of this work. We modeled data transmission scheme as one-dimensional random walk and we express stationary probability distributions as a product form solution. We then study on the excessive packet rates and the system stability. We also consider the probability of a transmitted bit is correctly received by a receiver node that operates in a set of M identical sensor nodes with the existence of noise and interference. A numerical result show the effect of number of sensors in the network on interference values and transmission error probability.

Acknowledgments. We gratefully acknowledge the support of the ERA-NET ECROPS Project under EPSRC Grant No. EP=K017330=1 to Imperial College.

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References

- Yick, J., Mukherjee, B., Ghosal, D.: Wireless sensor network survey. Comput. Netw. 52(12), 2292–2330 (2008)
- Gao, T., Greenspan, D., Welsh, M., Juang, R., Alm, A.: Vital signs monitoring and patient tracking over a wireless network. In: 27th Annual International Conference of the Engineering in Medicine and Biology Society, IEEE-EMBS 2005, pp. 102– 105, January 2005
- 3. Hart, J.K., Martinez, K.: Environmental sensor networks: a revolution in the earth system science? Earth Sci. Rev. **78**(3), 177–191 (2006)
- Tiwari, A., Ballal, P., Lewis, F.L.: Energy-efficient wireless sensor network design and implementation for condition-based maintenance. ACM Trans. Sen. Netw. 3, 1–23 (2007)
- Yick, J., Mukherjee, B., Ghosal, D.: Analysis of a prediction-based mobility adaptive tracking algorithm. In: 2nd International Conference on Broadband Networks, BroadNets 2005, vol. 1, pp. 753–760, October 2005
- Hatler, M.: Industrial wireless sensor networks: trends and developments. Retrieved 11(14), 2013 (2013)
- Harrop, P., Das, R.: Wireless sensor networks 2010–2020. Networks 2010, 2020 (2010)
- Gelenbe, E.: A sensor node with energy harvesting. ACM SIGMETRICS Perform. Eval. Rev. 42(2), 37–39 (2014)

- Gelenbe, E.: Synchronising energy harvesting and data packets in a wireless sensor. Energies 8(1), 356–369 (2015)
- Gelenbe, E., Kadioglu, Y.M.: Performance of an autonomous energy harvesting wireless sensor. In: Abdelrahman, O.H., Gelenbe, E., Gorbil, G., Lent, R. (eds.) Information Sciences and Systems 2015. LNEE, vol. 363, pp. 35–43. Springer, Heidelberg (2016). doi:10.1007/978-3-319-22635-4.3
- 11. Gelenbe, E., Kadioglu, Y.M.: Energy loss through standby and leakage in energy harvesting wireless sensors. In: 20th IEEE International Workshop on Computer Aided Modelling and Design of Communication Links and Networks (2015)
- Kadioglu, Y.M., Gelenbe, E.: Packet transmission with K energy packets in an energy harvesting sensor. In: Proceedings of the 2nd International Workshop on Energy-Aware Simulation, ENERGY-SIM 2016, New York, NY, USA, pp. 1:1–1:6. ACM (2016)