A Study on the Statistical Estimation Framework of Energy Saving Effectiveness for Sensor Nodes of a Wireless Sensor Network

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Abstract

We propose a statistical estimation framework to assess energy saving effectiveness of the sensor nodes which have been deployed in a rough physical environment and consisted in a wireless sensor network by use of the Bayesian maximum likelihood estimation procedure. Accordingly, we formulate Bayesian maximum likelihood estimation framework for the system energy saving effectiveness of sensor nodes in a wireless sensor network using non-informative prior information about means of active and sleep times based on time frames of sensor nodes under the T-MAC which is known as most energy efficient CSMA contention-based MAC protocols.

1. Introduction

Sensor nodes in a wireless sensor network are usually powered by batteries. Energy consumption during node operation determines battery life and eventually sensor node life. Power consumption depends on the different hardware and software components in a sensor node of a wireless sensor network and their various activities. In order to determine the life of the battery and sensor node, it is important to assess the energy consumption amount of each sensor node of a wireless sensor network through observation of active and sleep time data. That is, we have to know the energy consumption amounts and time duration for sensor node activities including computations, sensing, and RF transmission and reception.

With this, it is important to reduce unnecessary activities of high energy-demands in sensor nodes of the wireless sensor network. The wireless sensor network MAC protocols extend network lifetimes by reducing the activity of the highest energy-demanding component of the sensor platform with the radios. Trading off network throughput and latency (delay), energy-efficient MAC protocols synchronize network communication to create opportunities for radios to sleep with active duty cycles as low as 2.5% under minimal traffic conditions. Understanding both normal and bad sources of energy loss is essential in designing a power control system. Recently the state-of-the-art wireless sensor network MAC protocols have been designed to optimize energy efficiency based on CSMA-CA (carrier sense multiple access with collision avoidance) and slotted contention [1-6]. For assessment of the energy consumption of sensor nodes at the assigned time, we develop energy saving effectiveness assessment models for observed active and sleep times data based on time frames of sensor nodes under T-MAC which is known as most energy efficient CSMA contention-based MAC protocol in many experiments.

In this paper, we propose a statistical estimation framework to assess system energy saving effectiveness by use of observed active and sleep times data based on time frames of sensor nodes under T-MAC protocol in terms of classical and Bayesian estimation procedures under non-informative prior information about means of active and sleep times based on time frames of sensor nodes in a wireless sensor network. Also we apply the proposed Bayesian maximum likelihood estimators of system energy saving effectiveness in the wireless sensor network consisting of five (5) sensor nodes (Kmote units) under T-MAC protocol during 1,500 seconds assuming that designed events are occurred and monitored.

2. A Sensor Node and Its Energy Consumption

A wireless sensor node (or simply sensor node) consists of sensing, computing, communication, and power components. These components are integrated on a single or multiple boards, and packaged in a few cubic inches. With state-of-the-art, low-power circuit and networking technologies, a sensor node powered by two (2) AA batteries can last for up to three years with a 1% low duty cycle working mode.

The main components of a sensor node are micro-controller (processor and memory storage), transceiver, external memory, power unit and one or more sensors with analog to digital converter as shown in Figure 1.

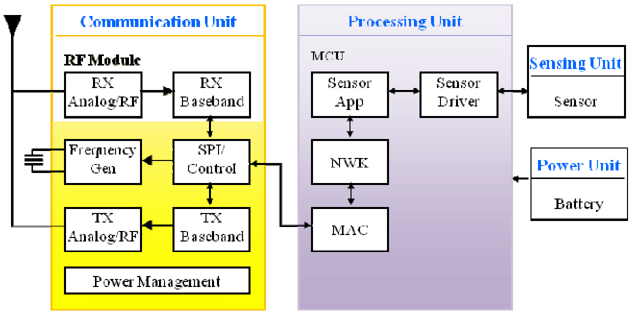

Figure 1. Main Components of a Sensor Node

A model for prediction of the current energy state of the battery of a sensor node based on the historical data according to the use of the sensor node was proposed by Tim Nieberg et al [7]. The model considers the three main components of a sensor node that reduce the energy stored in the batteries such as the radio and transceiver, the processor, and the actual sensing device as summarized in Table 1.

Table 1. Three Main Factors of Energy Consumption of a Sensor Node

Factor	Classified States	Description
Radio and Transceiver	*off*, *sleep*, *receiving*, and *transmitting*	For these four states, the energy consumption depends on the time.
Processor	*off*, *sleep*, *idle*, and *active*	In sleep mode, the CPU and most internal peripherals are turned off, and can be woken by an external event (interrupt) only. In idle mode, the CPU is still inactive, but now some peripherals are active. Within the active states, the CPU and all peripherals are active. In the active state, multiple sub-states may be defined based on clock speeds and voltages.
Sensor	*on* and *off*	The energy consumption within both states can be measured by time. However, more powerful sensor work in different states, comparable to the processor, and need to be modeled by more states.

The communication function between nodes is realized by a RFM TR1001 hybrid radio transceiver that is very suitable for the energy consumption experiment. It has low power consumption and has small size. The TR1001 supports transmission rates up to 115.2 Kbps. The power consumption during receive is approximately 14.4mW, during transmit 16.0mW, and in sleep mode 15.0 μW (0.015 mW) [8-10]. The transmitter output power is maximal 0.75 mW. Experimental results of power consumption of MICA and Rockwell's Wins motes are shown in Table 2.

Table 2. Energy Analysis of the Sensor Motes

Unit	State	Approximately Power Dissipation (mW)	
		MICA	Rockwell's Wins
Processor (MCU)	Active	5	360
	Sleep	1.2	41
	Idle	-	-
	Off	0.02	0.9
Sensor	On	4.7	23
	Off	-	-
Radio and Transceiver	Transmitting (TX)	25	1080
	Receiving (RX)	22	750
	Sleep	0.02	64
	Off	-	-

Most of MICA motes are equipped two (2) 1.5V AA batteries for their power supply. This means MICA motes can last only 13.2 days @25 *mW* if they operate full TX/RX modes. Also MICA motes can last 330 days @1 *mW*. For 5 years' of sensor node lifetime, the power consumption must be reduced up to 180 μW.

The power consumption of sensor node is strongly dependent on the operating mode. In MICA mote, proportional power consumption can be represented as follows:

TX: RX: Sleep = 25mW: 22mW: 0.02mW.

As same manner, proportional power consumption of Rockwell's Wins can be expressed as follows:

TX: RX: Sleep = 1080mW: 750mW: 64mW.

Idle mode of the radio and transceiver shows that it consumes almost as much power as RX mode of radio and transceiver. In order to reduce power consumption and extend lifetime of sensor nodes, radio needs to be completely shut off when sensor networks idle time dominates. Each sensor node has limited by power supply because sensor nodes may not be rechargeable of battery. Most energy consumption occurred from communication unit as depicted in Figure 2.

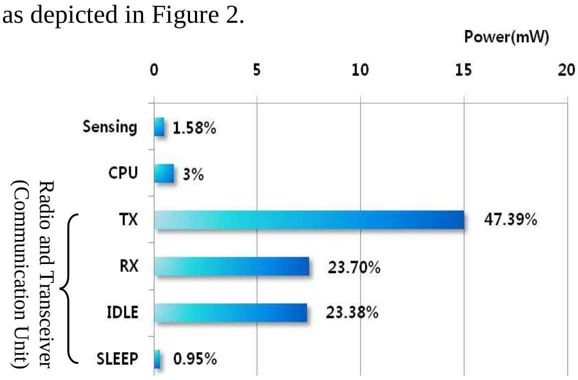

Figure 2. Energy Consumption Proportions of Sensor Node Units

With these experimental results of energy consumption of several sensor nodes, it can be disregarded a little amount (0.95%) of energy consumption in sleep mode of radio and transceiver and another little amount (4.58%) of energy consumption in sensor and processor for a large amount (94.47%) of energy consumption in transmitting, receiving and idle of radio and transceiver in communication unit [11-13].

3. Statistical Estimation Framework for Active and Sleep Times Data from the Sensor Nodes

Timeout MAC (T-MAC) is a contention-based MAC layer protocol that builds upon the successes of S-MAC in optimizing power efficiency for the sensor network by sleeping during periodic network inactivity. The T-MAC protocol introduces a listening timeout mechanism that improves on the idle listening overhead by dynamically adapting the active listening period in response to network traffic. T-MAC permits sensor nodes to sleep as soon as all network traffic has completed.

As shown in Figure 3, the end of traffic is signaled by monitoring an idle channel for an adaptive timeout (TA) period. The TA period represents the longest period in which a hidden node would have to wait before hearing the first bit of a CTS (clear to send) message. This timeout waiting period is decomposed into the largest contention window ( ), the time to send an RTS (request to send) message ( ), and the protocol small inter-frame spacing (SIFS) delay before the receiving CTS node can process a response to the RTS.

We consider a deployed wireless sensor network system for continuous sensing, event detection, and monitoring consisting of N non-identical sensor nodes each of which has exponentially distributed active and sleep times under the lifetime frames of a wireless sensor network under T-MAC protocol at the data-link layer.

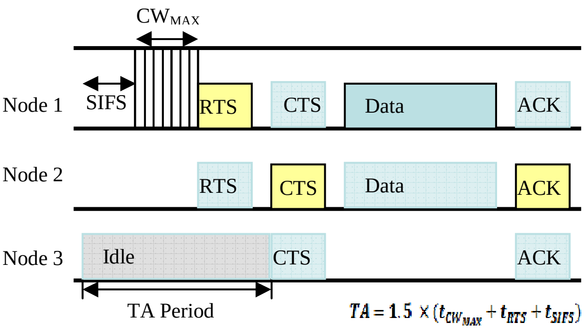

Figure 3. T-MAC Dynamic Sleep Schedule with Adaptive Timeout Period

The random sample data of active and sleep times from deployed sensor nodes can be collected from indicators as the energy consumption depends on the time which has been mainly two states, active or sleep [14-17].

For sensor node, if we suppose that active/sleep frame cycles (slots) are observed as lifetimes, then are observed active times and are observed sleep times data on the frame of sensor nodes as shown in Figure 4.

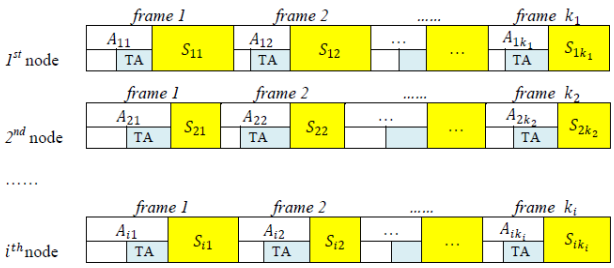

Figure 4. Active and Sleep Times Data of T-MAC Protocol

More precisely, for sensor node, if we suppose that active/sleep frame cycles (slots) are observed as lifetimes, then are independent active times random sample data from the exponential distribution with the mean time between active times (MTBA) and are independent sleep times random sample data from the exponential distribution) with the mean time between sleep times (MTBS) , and the component energy saving effectiveness of the sensor node is given by

(1)

According to Sandler, the system energy saving un-effectiveness of a wireless sensor network is the product of the component energy saving un-effectiveness of the sensor node, that is,

(2)

Therefore, the system effectiveness in energy saving of a wireless sensor network which are consisting of N non-identical sensor nodes becomes

(3)

where is MTBA and is MTBS of the sensor node.

If we assume that the active times { } for the N non-identical sensor nodes are exponentially distributed with Mean Times between Actives (MTBA's) , respectively, such that

(4)

where, is the active time of the sensor

node for $j = 1, \ldots, k_i$, $\theta_i(> 0)$ is the Mean Time Between Actives (MTBA) of the i^{th} sensor node, k_i = number of the observed active/sleep cycles (slots) of the i^{th} sensor node, for $i = 1, \ldots, N$.

Also if we assume that the sleep times $\{S_{i1,}S_{i2,} \ldots, S_{ik_i}\}$ for the N non-identical sensor nodes are exponentially distributed with Mean Times Between Sleeps (MTBS's) $\mu_{1,}\mu_{2,} \ldots, \mu_N$, respectively, such that

$$f_2(S_{ij}|\mu_i) = \frac{1}{\mu_i} exp\left(-\frac{S_{ij}}{\mu_i}\right), \tag{5}$$

where, $S_{ij}(> 0)$ is the j^{th} sleep time of the i^{th} sensor node, for $j = 1, \ldots, k_i$, $\mu_i(> 0)$ is the Mean Time Between Sleeps (MTBS) of the i^{th} sensor node, k_i = number of the observed active/sleep cycles (slots) of the i^{th} sensor node, for $i = 1, \ldots, N$.

For i^{th} sensor node, we obtain the likelihood function of T_{A_i} and T_{S_i}, given θ_i and μ_i.as follows.

$$L_i(\theta_i, \mu_i|T_{A_i}, T_{S_i}) = \prod_{j=1}^{k_i} f_1(A_{ij}|\theta_i)\, f_2(S_{ij}|\mu_i)$$
$$= \prod_{j=1}^{k_i} \frac{1}{\theta_i} exp\left(-\frac{A_{ij}}{\theta_i}\right) \frac{1}{\mu_i} exp\left(-\frac{S_{ij}}{\mu_i}\right)$$
$$= \frac{1}{(\theta_i\mu_i)^{k_i}} exp\left[-\left(\frac{T_{A_i}}{\theta_i} + \frac{T_{S_i}}{\mu_i}\right)\right], \tag{6}$$

where, k_i = number of the observed active/sleep cycles (slots) of the i^{th} sensor node, T_{A_i}= total operating time observed; $T_{A_i} = \sum_{j=1}^{k_i} A_{ij}$, where A_{ij} is the j^{th} active time of the i^{th} sensor node, and T_{S_i}= total sleep time observed; $T_{S_i} = \sum_{j=1}^{k_i} S_{ij}$, where S_{ij} is the j^{th} sleep time of the i^{th} sensor node, for $i = 1, \ldots, N$.

By the Jeffrey's rule [20] based on Fisher's information matrix [18], two general classes of the noninformative prior distributions of the MTBA θ_i and MTBS μ_i for the i^{th} sensor are given by

$$g_{1i}(\theta_i) \propto \frac{1}{\theta_i^{u_i}}, \quad \theta_i > 0,\ u_i > 0 \text{, and} \tag{7}$$

$$g_{2i}(\mu_i) \propto \frac{1}{\mu_i^{v_i}}, \quad \mu_i > 0,\ v_i > 0 \text{, respectively.} \tag{8}$$

From the noninformative prior distributions in (7) and (8), and the likelihood function in (6), we can calculate joint posterior distribution of θ_i and μ_i for the i^{th} sensor node as follows.

$$\bar{f}_i(\theta_i, \mu_i|T_{A_i}, T_{S_i})$$
$$= \frac{L_i(\theta_i, \mu_i|T_{A_i}, T_{S_i})}{\int_0^\infty \int_0^\infty L_i(\theta_i, \mu_i|T_{A_i}, T_{S_i})} \cdot \frac{g_{1i}(\theta_i) g_{2i}(\mu_i)}{g_{1i}(\theta_i) g_{2i}(\mu_i) d\theta_i d\mu_i}$$
$$= \frac{(T_{A_i})^{k_i+u_i-1}(T_{S_i})^{k_i+v_i-1}}{\Gamma(k_i+u_i-1)\Gamma(k_i+v_i-1)} \cdot \frac{exp\left[-\left(\frac{T_{A_i}}{\theta_i} + \frac{T_{S_i}}{\mu_i}\right)\right]}{\theta_i^{k_i+u_i}\mu_i^{k_i+v_i}}, \tag{9}$$

where $\theta_i > 0$, $\mu_i > 0$, and $\Gamma(\cdot)$ is a gamma function.

4. Bayesian Maximum Likelihood Estimators of System Energy Saving Effectiveness

Maximum likelihood estimation is a popular statistical method used for fitting a mathematical model to some sampling data. Modeling data of real world by estimating maximum likelihood offers a way of tuning the free parameters of the model to provide a good fit. The maximum likelihood estimator (MLE) selects the parameter value which gives the observed data the largest possible probability. Also if the parameter space $\hat{\Theta}$ consists of a number of components such as $\hat{\theta} = (\theta_1, \theta_2, \ldots, \theta_k)$, then we can define their separate maximum likelihood estimators θ_i^{ML} of θ_i, as the corresponding component of the MLE of the complete parameters $\hat{\theta} = (\theta_1, \theta_2, \ldots, \theta_k)$.

Let $\underline{x} = (x_1, x_{2,} \ldots, x_N)$ is a random sample vector of statistically independent observation of the random variables $\underline{X}$ from $f(x_i|\theta_i)$. The likelihood function for random sample is the joint probability function of $X_1, X_{2,} \ldots, X_N$, which is $L(\theta_i|\underline{x}) = \prod_{j=1}^{N} f(x_i|\theta_i)$, when considered as a function of θ_i. The maximum likelihood estimator (MLE) of θ_i is defined as the value θ_i^{ML} such that $L(\theta_i^{ML}|\underline{x}) \geq L(\theta_i|\underline{x})$ for every value of θ_i. That is, the MLE of θ_i is the value θ_i^{ML} that maximizes the likelihood function. If we use joint posterior distribution $f(\hat{\theta}|\underline{x})$ instead of likelihood function $L(\hat{\theta}|\underline{x})$ in maximum likelihood estimation, then we can obtain Bayes MLE $\hat{\theta}^{BML}$ of $\hat{\theta}$. While this is a Bayes estimator under the uniform loss function, it is not very representative of Bayesian methods in general, whereas usual Bayes estimators under squared-error loss function are characterized by the use of distributions to summarize data and draw inferences. However this Bayes MLE is more generalized that classical MLE.

Maximizing the joint posterior distribution of θ_i and μ_i for i^{th} sensor node in (9) with respect to θ_i and μ_i, we have the Bayes MLE of θ_i and μ_i, respectively as follows.

The Bayes MLE of θ_i, denoted by θ_i^{BML}, can be evaluated from the value of θ_i that which satisfies the equation [19, 21, 22].

$$\frac{\partial}{\partial\theta_i} ln\, \bar{f}_i(\theta_i, \mu_i|T_{A_i}, T_{S_i}) = 0. \tag{10}$$

Also, the Bayes MLE of μ_i, denoted by μ_i^{BML}, can be evaluated from the value of μ_i that which satisfies

$$\frac{\partial}{\partial \mu_i} ln\ \bar{f}_i(\theta_i, \mu_i | T_{A_i}, T_{S_i}) = 0. \tag{11}$$

Hence, we get

$$\theta_i^{BML} = \frac{T_{A_i}}{k_i+u_i} \text{ and } \mu_i^{BML} = \frac{T_{S_i}}{k_i+v_i}, \text{ respectively.} \tag{12}$$

By mean of (12), the Bayes MLE of component energy saving un-effectiveness of i^{th} sensor node under the noninformative priors is given by

$$\bar{Q}_i^{BML} = \frac{\theta_i^{BML}}{\theta_i^{BML} + \mu_i^{BML}} = \frac{(k_i + v_i)T_{A_i}}{(k_i + v_i)T_{A_i} + (k_i + u_i)T_{S_i}}. \tag{13}$$

Therefore, by means of (2), (3) and (13), the Bayes MLE of system energy saving effectiveness of a wireless sensor network under the noninformative priors is given by

$$Q^{BML} = 1 - \prod_{i=1}^{N} \bar{Q}_i^{BML}$$

$$= 1 - \prod_{i=1}^{N} \frac{(k_i+v_i)T_{A_i}}{(k_i+v_i)T_{A_i}+(k_i+u_i)T_{S_i}}. \tag{14}$$

where, k_i = number of the observed active/sleep cycles (slots) of the i^{th} sensor node, T_{A_i}= total operating time observed; $T_{A_i} = \sum_{j=1}^{k_i} A_{ij}$, where A_{ij} is the j^{th} active time of the i^{th} sensor node, and T_{S_i}= total sleep time observed; $T_{S_i} = \sum_{j=1}^{k_i} S_{ij}$, where S_{ij} is the j^{th} sleep time of the i^{th} sensor node, for $i = 1, \ldots, N$.

5. Application of Proposed Bayesian MLEs of System Energy Saving Effectiveness

The observed sample data of active and sleep times from sensor nodes of a wireless sensor network which is shown in Figure 5 can be collected from a sink node as the base of the energy consumption depends on the time which has been mainly two states, active or sleep. We have observed active and sleep times data from five (5) among twenty one (21) sensor nodes (Kmote units) under T-MAC protocol during 1,500 seconds assuming that designed events are occurred and monitored as summarized in Table 3.

Figure 5. A Wireless Sensor Network System with Kmote Units which used for the Study

Table 3. Observed Active and Sleep Times Data from Five (5) Sensor Nodes

Node	A_1 (TA1.)	S_1	A_2 (TA2.)	S_2	A_3 (TA3.)	S_3	A_4 (TA4.)
1	30 (10)	360	120 (0)	300	30 (10)	540	120 (10)
2	70 (10)	400	205 (10)	595	80 (10)	150	0 (0)
3	200 (0)	665	155 (30)	300	55 (10)	90	35 (0)
4	90 (15)	325	125 (0)	335	70 (10)	440	115 (10)
5	170 (20)	445	200 (15)	400	80 (10)	150	55 (0)

Unit: *sec* (second)

From (14), we can calculate the Bayesian maximum likelihood estimates of system energy saving effectiveness of a wireless sensor network under the noninformative prior information according to the parameters $u_i(> 0) = 0.1(0.3)1.0, 2(2)8$ and $v_i(>0)$=0.1(0.3)1.0, 2(2)8 as summarized in Table 4.

Table 4. Bayes Maximum Likelihood Estimates of System Energy Saving Effectiveness

(a) u_i=0.1(0.3)1.0 and v_i=0.1(0.3)1.0

Q^{BML}	u_i=0.1	u_i=0.4	u_i=0.7	u_i=1.0
v_i=0.1	0.7007	0.6995	0.6457	0.6278
v_i=0.4	0.6987	0.6876	0.6324	0.5967
v_i=0.7	0.6499	0.6234	0.6008	0.5876
v_i=1.0	0.6312	0.6108	0.5996	0.5692

(b) u_i=2(2)8 and v_i=2(2)8

Q^{BML}	u_i=2	u_i=4	u_i=6	u_i=8
v_i=2	0.8007	0.8195	0.8457	0.8878
v_i=4	0.8187	0.8246	0.8326	0.8900
v_i=6	0.8495	0.8534	0.8708	0.8986
v_i=8	0.8515	0.8798	0.8893	0.9002

6. Conclusions

In order to reduce energy consumption at sensor nodes, significant researches have been carried out on the design of low-power sensor devices. But due to fundamental hardware limitations, energy efficiency can only be achieved through the design of energy efficient communication protocols such as the sensor MAC (S-MAC), Timeout MAC (T-MAC), Berkeley MAC (B-MAC), and Dynamic Sensor MAC (DS-MAC) and so on. The main reasons of energy wastes among these MAC protocols based on contention are collision, overhearing, control packet overhead, idle listening, and over-remitting.

With this, we need to estimate system energy saving effectiveness according to energy efficient MAC protocols. This paper formulates a statistical estimation framework to assess system energy saving effectiveness by use of observed active and sleep times data based on time frames of sensor nodes under T-MAC protocol in terms of classical and Bayesian estimation procedures under non-informative prior information about means of active and sleep times based on time frames of sensor nodes in a wireless sensor network.

After application of the proposed Bayesian maximum likelihood estimators of system energy saving effectiveness in the wireless sensor network consisting of five (5) which are related to events among twenty one (21) sensor nodes (Kmote units) under T-MAC protocol, we have the following results:

(1) We recognized that the proposed Bayesian maximum likelihood estimators of system energy saving effectiveness are excellent to adapt in evaluation of energy efficient contention-based MAC protocols using noninformative prior knowledge from previous experience.

(2) The proposed Bayesian maximum likelihood estimators are robust and stable in utilization as an evaluation tool for the system energy saving effectiveness in a wireless sensor network.

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