Journal of Korea Multimedia Society Vol. 13, No. 6, JUNE 2010(pp. 890-900)

Bayesian Statistical Modeling of System Energy Saving Effectiveness for MAC Protocols of Wireless Sensor Networks: The Case of Non-Informative Prior Knowledge

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ABSTRACT

The Bayesian networks methods provide an efficient tool for performing information fusion and decision making under conditions of uncertainty. This paper proposes Bayes estimators for the system effectiveness in energy saving of the wireless sensor networks by use of the Bayesian method under the non-informative prior knowledge about means of active and sleep times based on time frames of sensor nodes in a wireless sensor network. And then, we conduct a case study on some Bayesian estimation models for the system energy saving effectiveness of a wireless sensor network, and evaluate and compare the performance of proposed Bayesian estimates of the system effectiveness in energy saving of the wireless sensor network. In the case study, we have recognized that the proposed Bayesian system energy saving effectiveness estimators are excellent to adapt in evaluation of energy efficiency using non-informative prior knowledge from previous experience with robustness according to given values of parameters.

Key words: Wireless sensor network, MAC protocols, Bayesian analysis, system effectiveness

1. INTRODUCTION

The wireless sensor network (WSN) is a network of sensor nodes communicating by means of wireless transmission. WSN is a wireless network consisting of spatially distributed autonomous sensor devices which are called sensor nodes in remote setting to cooperatively monitor physical or environmental conditions, such as temperature, sound, vibration, pressure, motion or pollutants, at different environments. The WSN nodes operate on battery power which is often deployed in a rough physical environment as some networks many consists of hundreds to thousands of nodes.

The media access control (MAC) protocols of WSN extend network lifetimes by reducing the activity of the highest energy-demanding component of the sensor platform. Trading off network throughput and latency, energy efficient MAC protocols synchronize network communication to create opportunities for radios to sleep with active duty cycles [1-4].

Significant researches have been carried out to reduce energy consumption at sensor nodes through 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

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Receipt date : May 27, 2010, Revision date : June 21, 2010
Approval date : July 7, 2010
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※ This work was supported by the Pukyong National University Research Fund in 2008 (PK-2008-028).

such as the sensor MAC, Timeout MAC, Berkeley MAC, Dynamic Sensor MAC, Dynamic MAC and so on [5-7,13-15].

The system effectiveness in energy saving is the probability that the wireless sensor network system can successfully meet an energy saving operational demand within a given time period when operated under specific conditions.

Bayesian methods provide an efficient tool to analyze the system effectiveness in energy saving of the wireless sensor networks. Bayesian methods got their name from the Rev. Thomas Bayes, who wrote an essay, posthumously published in 1763, that offered a mathematical formula for calculating probabilities among several variables that are causally related but for which-unlike calculating the probability of a coin landing on heads or tails-the relationships can't easily be derived by experimentation. But it was the rapid progress in computer power and the development of key mathematical equations that made it possible for the first time, in the late 1980s, to compute Bayesian method with enough variables that they were useful in practical applications. The Bayesian approach filled a void in the decades and long effort to add intelligence to computers. Nowadays Bayesian methods reign supreme as the most effective set of methods to use for a vast range of inductive inference problems. Recently Bayesian data analysis methods for modeling informative estimation and evaluation of network systems which is called Bayesian networks have become increasingly and rapidly important in the WSN [8-12,17].

This paper is an extension of [18] which we studied in the case of conjugate prior knowledge. In this paper, under the consideration of the non-informative prior knowledge based on observed active and sleep times data from sensor nodes in a wireless sensor network, we develop Bayesian statistical models for observed active and sleep times data based on time frames of sensor nodes under the selected energy efficient CSMA contention-based MAC protocols such as S-MAC (sensor MAC), T-MAC (Timeout MAC), B-MAC (Berkeley MAC), DS-MAC (Dynamic Sensor MAC), and D-MAC (Dynamic MAC) based on IEEE 802.15.4 for wireless sensor networks. Also we propose Bayesian estimation procedures for system effectiveness in energy saving for the selected energy efficient MAC protocols.

Accordingly, we propose Bayes estimators for the system effectiveness in energy saving of the wireless sensor networks by use of the Bayesian method under the non-informative prior knowledge about means of active and sleep times based on time frames of sensor nodes, and then we evaluate and compare the performance of proposed Bayesian estimates of the system effectiveness in energy saving of the wireless sensor network.

2. BAYESIAN LIFETIMES FRAMEWORK FOR PARAMETERS OF SYSTEM ENERGY SAVING EFFECTIVENESS

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

More precisely, for i^{th} deployed sensor node, if we suppose that k_i active/sleep frame cycles (slots) are observed as lifetimes, then $A_{i1}, A_{i2}, \cdots, A_{ik_i}$ are independent active times random sample data from the exponential distribution $\epsilon(\theta_i)$ with the mean time between active times (MTBA) θ_i and $S_{i1}, S_{i2}, \cdots, S_{ik_i}$ are independent sleep times random sample data from the exponential distribution $\epsilon(\mu_i)$ with the mean time between sleep times (MTBS) μ_i and the component energy saving effectiveness of the i^{th} deployed sensor node is given by

$$Q_i = \frac{\mu_i}{\theta_i + \mu_i}. \quad (1)$$

The system effectiveness in energy saving (or system energy saving effectiveness) is defined as the probability that the wireless sensor network system can successfully meet an energy saving operational demand within a given time period when operated under specific conditions. According to Sandler [16], the system energy saving un-effectiveness of a wireless sensor network is the product of the component energy saving un-effectiveness of the i^{th} sensor node, that is,

$$\bar{Q} = \prod_{i=1}^{N} \bar{Q}_i = \prod_{i=1}^{N}(1 - \frac{\mu_i}{\theta_i+\mu_i}) = \prod_{i=1}^{N}(\frac{\theta_i}{\theta_i+\mu_i}) \tag{2}$$

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

$$Q = 1 - \bar{Q} = 1 - \prod_{i=1}^{N}(\frac{\theta_i}{\theta_i+\mu_i}), \tag{3}$$

where, θ_i is MTBA and μ_i is MTBS of the i^{th} sensor node.

The fundamental tool used for Bayesian estimation is Bayes' theorem. The likelihood function is the function through which the observed lifetimes results or samples (active and sleep times) from the deployed sensor nodes modify prior knowledge of the system effectiveness. The prior distribution represents all information that is known or assumed about the system effectiveness in energy saving. The posterior distribution is a modified and updated version of the previous information expressed by the prior distribution on the basis of the observed lifetimes results or samples from the deployed sensor nodes of a wireless sensor network.

We can write Bayes' theorem in a mathematical expression as Posterior distribution = Prior distribution × Likelihood Function/Marginal Distribution. That is,

$$f(\hat{\theta}|\underline{x}) = \frac{[\prod_{i=1}^{N} f(x_i|\hat{\theta})]\, g(\hat{\theta})}{f(x)} = \frac{f(\underline{x}|\hat{\theta})g(\hat{\theta})}{f(\underline{x})} = \frac{g(\hat{\theta})L(\hat{\theta}|\underline{x})}{\int_{\hat{\Theta}} g(\hat{\theta})L(\hat{\theta}|\underline{x})d\hat{\theta}}, \text{if } \hat{\theta}\text{: continuous,} \tag{4}$$

where, $\hat{\theta} = (\theta_1, \theta_2, ..., \theta_k)$ is a vector of the parameter space $\hat{\Theta}$, $\underline{x} = (x_1, x_2, ..., x_N)$ is a vector of statistically independent observation of the random variables $\underline{X}$ (*the sample data*), $g(\hat{\theta})$ is the joint prior probability distribution of $\hat{\Theta}$ (*the prior knowledge*), $f(x_i|\hat{\theta})$ is the conditional probability distribution of X_i given $\hat{\theta}$ (*the sampling model*), $f(\underline{x}|\hat{\theta}) = \prod_{i=1}^{N} f(x_i|\hat{\theta}) = L(\hat{\theta}|\underline{x})$ is the joint conditional probability distribution of $\underline{X}$ given $\hat{\theta}$ (*the likelihood function* of $\hat{\theta}$ give $\underline{x}$), $f(\underline{x}, \hat{\theta})$ is the joint probability distribution of $\underline{X}$ and $\hat{\Theta}$, $f(x)$ is the marginal probability distribution of $\underline{X}$, and $f(\hat{\theta}|\underline{x})$ is the joint posterior probability distribution of $\hat{\theta}$ given $\underline{x}$ (*the Posterior model*)

If we assume that the active times $\{A_{i1}, A_{i2}, ..., A_{ik_i}\}$ for the N non-identical deployed sensor nodes are exponentially distributed with Mean Times Between Actives (MTBA's) $\theta_1, \theta_2, ..., \theta_N$, respectively, such that

$$f_1(A_{ij}|\theta_i) = \frac{1}{\theta_i} exp\left(-\frac{A_{ij}}{\theta_i}\right), \tag{5}$$

where $A_{ij}(>0)$ is the j^{th} active time of the i^{th} sensor node for $j = 1, ..., k_i$, $\theta_i(>0)$ 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 $i = 1, ..., N$.

Also if we assume that the sleep times $\{S_{i1}, S_{i2}, ..., S_{ik_i}\}$ for the N non-identical deployed sensor nodes are exponentially distributed with Mean Times Between Sleeps (MTBS's) $\mu_1, \mu_2, ..., \mu_N$, respectively, such that

$$f_2(S_{ij}|\mu_i) = \frac{1}{\mu_i} exp\left(-\frac{S_{ij}}{\mu_i}\right), \tag{6}$$

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

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.

$$L_i(\theta_i,\mu_i|T_{A_i},T_{S_i}) = \prod_{j=1}^{k_i} f_1(A_{ij}|\theta_i)\, f_2(S_{ij}|\mu_i)$$

$$= \prod_{j=1}^{k_i} \frac{1}{\theta_i} exp\left(-\frac{A_{ij}}{\theta_i}\right)\frac{1}{\mu_i} exp\left(-\frac{S_{ij}}{\mu_i}\right)$$

$$= \frac{1}{(\theta_i\mu_i)^{k_i}} exp\left[-(\frac{T_{A_i}}{\theta_i}+\frac{T_{S_i}}{\mu_i})\right], \tag{7}$$

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

3. NON-INFORMATIVE PRIOR KNOWLEDGE OF PARAMETERS OF SYSTEM ENERGY SAVING EFFECTIVENESS

The prior distribution as a prior knowledge of parameters can be chosen to represent the beliefs or experience of the researchers or engineers before observing the results or samples of an experiment. However, it is hard for a researchers or engineers to specify prior beliefs or experience about parameters, and to cast them into the form of a prior probability distribution.

A non-informative prior knowledge is a function which is used in place of a subjective prior distribution when little or no prior information is available. The term "non-informative" is used to involve the lack of subjective beliefs or experience used in formulating such a prior knowledge. However, one can think of a non-informative prior as simply being a function that is formally used in place of a subjective prior distribution, for the purpose of accomplishing some goals such robustness, flexibility and stability of parameters, and so on. Jeffreys [20] proposed a method of generating non-informative priors which is invariant to trans formations of the parameter vector. His method begins by considering the Fisher information matrix. This is known as Jeffrey's rule [20].

If $|I(\hat{\theta})|$ is the determinant of the Fisher's information matrix [21], then an approximate non-informative prior distribution of the parameter space $\hat{\Theta}$ is given by

$$g(\hat{\theta}) \propto |I(\hat{\theta})|^{\frac{1}{2}}, \tag{8}$$

where,

$$I(\hat{\theta}) = -E\left(\frac{\partial^2}{\partial\hat{\theta}^2} ln\, L(\hat{\theta}|\underline{x})\right).$$

Thus, by the Jeffrey's rule based on Fisher's information matrix, two general classes of the non-informative prior distributions of the MTBA θ_i and MTBS μ_i for the i^{th} sensor are given by

$$g_{1i}(\theta_i) \propto \frac{1}{\theta_i^{u_i}}, \quad \theta_i > 0,\ u_i > 0, \tag{9}$$

and

$$g_{2i}(\mu_i) \propto \frac{1}{\mu_i^{v_i}}, \quad \mu_i > 0,\ v_i > 0, \tag{10}$$

respectively.

From the non-informative prior distributions in (9) and (10), and the likelihood function in (7), we can calculate joint posterior distribution of θ_i and μ_i for the i^{th} sensor node as follows.

$$\bar{f}_{1i}(\theta_i,\mu_i|T_{A_i},T_{S_i})$$
$$= \frac{L_i(\theta_i,\mu_i|T_{A_i},T_{S_i})}{\int_0^\infty\int_0^\infty L_i(\theta_i,\mu_i|T_{A_i},T_{S_i})}\cdot\frac{g_{1i}(\theta_i)g_{2i}(\mu_i)}{g_{1i}(\theta_i)g_{2i}(\mu_i)d\theta_i d\mu_i}$$
$$= \frac{(\theta_i\mu_i)^{-k_i} exp\left[-(\frac{T_{A_i}}{\theta_i}+\frac{T_{S_i}}{\mu_i})\right]}{\int_0^\infty\int_0^\infty(\theta_i\mu_i)^{-k_i} exp\left[-(\frac{T_{A_i}}{\theta_i}+\frac{T_{S_i}}{\mu_i})\right]}\cdot\frac{\theta_i^{-u_i}\mu_i^{-v_i}}{\theta_i^{-u_i}\mu_i^{-v_i}d\theta_i d\mu_i}$$
$$= \frac{\theta_i^{-(k_i+u_i)}\mu_i^{-(k_i+v_i)} exp\left[-(\frac{T_{A_i}}{\theta_i}+\frac{T_{S_i}}{\mu_i})\right]}{\int_0^\infty\int_0^\infty \theta_i^{-(k_i+u_i)}\mu_i^{-(k_i+v_i)} exp\left[-(\frac{T_{A_i}}{\theta_i}+\frac{T_{S_i}}{\mu_i})\right]d\theta_i d\mu_i}$$
$$= \frac{\theta_i^{-(k_i+u_i)}\mu_i^{-(k_i+v_i)} exp\left[-\left(\frac{T_{A_i}}{\theta_i}+\frac{T_{S_i}}{\mu_i}\right)\right]}{\left[\int_0^\infty \theta_i^{-(k_i+u_i)} exp\left(-\frac{T_{A_i}}{\theta_i}\right)d\theta_i\right]\cdot\left[\int_0^\infty \mu_i^{-(k_i+v_i)} exp\left(-\frac{T_{S_i}}{\mu_i}\right)d\mu_i\right]} \tag{11}$$

Letting $\theta_i = 1/z$ and using $\int_0^\infty z^{a-1} exp(-tz) dz = t^{-a}\Gamma(a)$, the integration calculation, the left side of the denominator of (11), is calculated as

$$\int_0^\infty \theta_i^{-(k_i+u_i)} exp(-T_{A_i}/\theta_i) d\theta_i = \int_0^\infty z^{k_i+u_i-2} exp(-T_{A_i} z) dz = \frac{\Gamma(k_i+u_i-1)}{(T_{A_i})^{k_i+u_i-1}}. \quad (12)$$

And, letting $\mu_i = 1/\beta$, the right side of the denominator of (11) can be calculated as

$$\int_0^\infty \mu_i^{-(k_i+v_i)} exp(-T_{S_i}/\mu_i) d\mu_i = \int_0^\infty \beta^{k_i+v_i-2} exp(-T_{S_i}\beta) d\beta = \frac{\Gamma(k_i+v_i-1)}{(T_{S_i})^{k_i+v_i-1}}. \quad (13)$$

Hence by the expressions (12) and (13), we can obtain joint posterior distribution of θ_i and μ_i for the i^{th} sensor node,

$$\bar{f}_{1i}(\theta_i, \mu_i | T_{A_i}, T_{S_i}) = \frac{(T_{A_i})^{k_i+u_i-1}(T_{S_i})^{k_i+v_i-1}}{\Gamma(k_i+u_i-1)\Gamma(k_i+v_i-1)} \cdot \frac{exp[-(\frac{T_{A_i}}{\theta_i} + \frac{T_{S_i}}{\mu_i})]}{\theta_i^{k_i+u_i}\mu_i^{k_i+v_i}}, \quad (14)$$

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

4. BAYESIAN ESTIMATION PROCEDURE OF SYSTEM ENERGY SAVING EFFECTIVENESS UNDER NON-INFORMATIVE PRIOR KNOWLEDGE

Under the non-informative prior knowledge, the Bayes point estimator of the system effectiveness in energy saving of the deployed sensor nodes of a wireless sensor network by means of MAC protocols can be calculated by the posterior distribution of the component energy saving un-effectiveness of i^{th} sensor node.

First, we have to find the posterior distribution of $\delta_i = \mu_i/\theta_i$ as the ratio of MTBS to MTBA. According to (14), we can express that

$$\bar{g}_{1\delta_i}(\delta_i | T_{A_i}, T_{S_i}) = \int_0^\infty \bar{f}_{1i}(\theta_i, \theta_i\delta_i | T_{A_i}, T_{S_i})\theta_i d\theta_i$$
$$= \frac{(T_{A_i})^{k_i+u_i-1}(T_{S_i})^{k_i+v_i-1}}{\Gamma(k_i+u_i-1)\Gamma(k_i+v_i-1)} \cdot \int_0^\infty (\theta_i)^{-(k_i+u_i-1)}(\theta_i\delta_i)^{-(k_i+v_i)} exp[-(\frac{T_{A_i}}{\theta_i} + \frac{T_{S_i}}{\theta_i\delta_i})]d\theta_i$$
$$= \frac{(T_{A_i})^{k_i+u_i-1}(T_{S_i})^{k_i+v_i-1}\delta_i^{-(k_i+v_i)}}{\Gamma(k_i+u_i-1)\Gamma(k_i+v_i-1)} \cdot \int_0^\infty \theta_i^{-(2k_i+u_i+v_i-1)} exp[-\frac{1}{\theta_i}(\frac{T_{S_i}}{\delta_i} + T_{A_i})]d\theta_i.$$

Letting $z = 1/\theta_i$ and using the formula $\int_0^\infty z^{a-1} exp(-tz) dz = t^{-a}\Gamma(a)$, we obtain

$$\bar{g}_{1\delta_i}(\delta_i | T_{A_i}, T_{S_i})$$
$$= \frac{(T_{A_i})^{k_i+u_i-1}(T_{S_i})^{k_i+v_i-1}\delta_i^{-(k_i+v_i)}}{\Gamma(k_i+u_i-1)\Gamma(k_i+v_i-1)} \cdot \int_0^\infty z^{(2k_i+u_i+v_i-2)-1} exp[-(\frac{T_{S_i}}{\delta_i} + T_{A_i})z]dz$$
$$= \frac{(T_{A_i})^{k_i+u_i-1}(T_{S_i})^{k_i+v_i-1}\delta_i^{-(k_i+v_i)}}{\Gamma(k_i+u_i-1)\Gamma(k_i+v_i-1)} \cdot \frac{\Gamma(2k_i+u_i+v_i-2)}{(\frac{T_{S_i}}{\delta_i} + T_{A_i})^{2k_i+u_i+v_i-2}}$$
$$= \frac{(T_{A_i})^{k_i+u_i-1}(T_{S_i})^{k_i+v_i-1}\delta_i^{k_i+u_i-2}}{\Gamma(k_i+u_i-1)\Gamma(k_i+v_i-1)} \cdot \frac{\Gamma(2k_i+u_i+v_i-2)}{(T_{S_i} + \delta_i T_{A_i})^{2k_i+u_i+v_i-2}}$$
$$= \frac{(T_{A_i})^{k_i+u_i-1}(T_{S_i})^{k_i+v_i-1}}{B(k_i+u_i-1,\ k_i+v_i-1)} \cdot \frac{\delta_i^{k_i+u_i-2}}{(T_{S_i} + \delta_i T_{A_i})^{2k_i+u_i+v_i-2}}.$$

Accordingly, the posterior distribution of the component energy saving un-effectiveness $\bar{Q}_i$ for i^{th} sensor node is given by

$$\bar{g}_{1i}(\bar{Q}_i | T_{A_i}, T_{S_i}) = \bar{g}_{1\delta_i}(\bar{Q}_i^{-1} - 1 | T_{A_i}, T_{S_i})\bar{Q}_i^{-2}$$
$$= \frac{(T_{A_i})^{k_i+u_i-1}(T_{S_i})^{k_i+v_i-1}}{B(k_i+u_i-1,\ k_i+v_i-1)} \cdot \frac{(\bar{Q}_i^{-1} - 1)^{k_i+u_i-2}\bar{Q}_i^{-2}}{[T_{S_i} + (\bar{Q}_i^{-1} - 1)T_{A_i}]^{2k_i+u_i+v_i-2}}$$
$$= \frac{(T_{S_i}/T_{A_i})^{k_i+v_i-1}}{B(k_i+u_i-1,\ k_i+v_i-1)} \cdot \frac{(1-\bar{Q}_i)^{k_i+u_i-2}(\bar{Q}_i)^{k_i+v_i-2}}{[1 - \bar{Q}_i(1 - \frac{T_{S_i}}{T_{A_i}})]^{2k_i+u_i+v_i-2}}$$
$$= \frac{(T_{S_i}/T_{A_i})^{k_i+v_i-1}}{B(k_i+u_i-1,\ k_i+v_i-1)} \cdot (\bar{Q}_i)^{k_i+v_i-2}(1-\bar{Q}_i)^{k_i+u_i-2}[1 - \bar{Q}_i(1 - T_{S_i}/T_{A_i})]^{-(2k_i+u_i+v_i-2)}, \quad (15)$$

where $0<\overline{Q_i}=\frac{1}{1+\delta_i}<1$, B(.,.) is a beta function and $\delta_i=\mu_i/\theta_i$ is the service factor.

Under the squared-error loss and the non-informative priors, Bayes point estimator of the i^{th} component energy saving un-effectiveness $\overline{Q_i}$ for the deployed sensor nodes of a wireless sensor network is the mean of the posterior distribution of $\overline{Q_i}$. We can find the Bayes point estimator of the i^{th} component energy saving un-effectiveness $\overline{Q_i}$ from the expression (15) and by use of transformation,

$$w=\frac{\bar{Q}_i\,(\frac{T_{S_i}}{T_{A_i}})}{1-\bar{Q}_i\,(1-\frac{T_{S_i}}{T_{A_i}})}. \tag{16}$$

Hence the Bayes estimator of the i^{th} component energy saving un-effectiveness $\overline{Q_i}$ can be calculated by the mean of the posterior distribution of $\overline{Q_i}$ as follows.

$$\begin{aligned}
\bar{Q}_i^{\,BE} &= E(\bar{Q}_i|T_{A_i},T_{S_i})\\
&=\int_0^1 \bar{Q}_i\bar{g}_{1i}(\bar{Q}_i|T_{A_i},T_{S_i})d\bar{Q}_i\\
&=\int_0^1 \frac{(T_{S_i}/T_{A_i})^{k_i+v_i-1}}{B(k_i+u_i-1,\ k_i+v_i-1)}\cdot\frac{(1-\bar{Q}_i)^{k_i+u_i-2}(\bar{Q}_i)^{k_i+v_i-1}}{[1-\bar{Q}_i(1-T_{S_i}/T_{A_i})]^{2k_i+u_i+v_i-2}}d\bar{Q}_i\\
&=\frac{(T_{S_i}/T_{A_i})^{k_i+v_i-1}}{B(k_i+u_i-1,\ k_i+v_i-1)}\cdot\int_0^1\frac{(1-\bar{Q}_i)^{k_i+u_i-2}(\bar{Q}_i)^{k_i+v_i-1}}{[1-\bar{Q}_i(1-T_{S_i}/T_{A_i})]^{2k_i+u_i+v_i-2}}d\bar{Q}_i\\
&=\frac{(T_{S_i}/T_{A_i})^{k_i+v_i-1}}{B(k_i+u_i-1,\ k_i+v_i-1)}\\
&\quad\times\int_0^1\left[\frac{1-w}{1-w\,(1-\frac{T_{A_i}}{T_{S_i}})}\right]^{k_i+u_i-2}\cdot\left[\frac{w\,(\frac{T_{A_i}}{T_{S_i}})}{1-w\,(1-\frac{T_{A_i}}{T_{S_i}})}\right]^{k_i+v_i-1}\\
&\quad\cdot\left[1-w\left(1-\frac{T_{A_i}}{T_{S_i}}\right)\right]^{2k_i+u_i+v_i-2}\cdot\frac{T_{A_i}}{T_{S_i}}\left[1-w(1-\frac{T_{A_i}}{T_{S_i}})\right]^{-2}dw\\
&=\frac{\left(\frac{T_{S_i}}{T_{A_i}}\right)^{k_i+v_i-1}}{B(k_i+u_i-1,\ k_i+v_i-1)}\cdot\left(\frac{T_{A_i}}{T_{S_i}}\right)^{k_i+v_i-1}\frac{T_{A_i}}{T_{S_i}}\\
&\quad\times\int_0^1 w^{k_i+v_i-1}\cdot(1-w)^{k_i+u_i-2}\cdot\left[1-w(1-\frac{T_{A_i}}{T_{S_i}})\right]^{-1}dw\\
&=\frac{\frac{T_{A_i}}{T_{S_i}}}{B(k_i+u_i-1,\ k_i+v_i-1)}\\
&\quad\cdot\int_0^1 w^{k_i+v_i-1}(1-w)^{k_i+u_i-2}\left[1-w(1-\frac{T_{A_i}}{T_{S_i}})\right]^{-1}dw\\
&=\frac{T_{A_i}}{T_{S_i}}\cdot\frac{k_i+v_i-1}{2k_i+u_i+v_i-2}\cdot {}_2F_1\left(1,k_i+v_i;2k_i+u_i+v_i-1;1-\frac{T_{A_i}}{T_{S_i}}\right),
\end{aligned} \tag{17}$$

where $0<\frac{T_{A_i}}{T_{S_i}}<2$ and

$${}_2F_1(a,b;c;t)=\sum_{i=0}^{\infty}\frac{(a)_i(b)_i}{(c)_i i!}t^i \tag{18}$$

is a confluent hyper-geometric function in Gauss' form for $|t|<1$, with $(a)_i=\frac{\Gamma(a+i)}{\Gamma(a)}$, $a, b, c>0$.

Therefore, under the non-informative prior knowledge, the Bayes point estimator Q^{BE} of the system energy saving effectiveness of the deployed sensor nodes of a wireless sensor network by means of MAC protocols can be represented as

$$\begin{aligned}
Q^{BE}&=1-\prod_{i=1}^{N}\bar{Q}_i^{\,BE}\\
&=1-\prod_{i=1}^{N}\left[\frac{T_{A_i}}{T_{S_i}}\cdot\frac{k_i+v_i-1}{2k_i+u_i+v_i-2}\cdot {}_2F_1\left(1,k_i+v_i;2k_i+\right.\right.\\
&\quad\left.\left.u_i+v_i-1;1-\frac{T_{A_i}}{T_{S_i}}\right)\right],
\end{aligned} \tag{19}$$

where $0<\frac{T_{A_i}}{T_{S_i}}<2$ and ${}_2F_1(a,b;c;t)$ is a confluent hyper-geometric function in Gauss' form for $|t|<1$ as expressed in (18).

5. SIMULATION STUDY OF THE PROPOSED BAYESIAN ESTIMATORS UNDER NON-INFORMATIVE PRIOR

We can generate active and sleep times as shown in Table 1 from 5 sensor nodes (Kmote

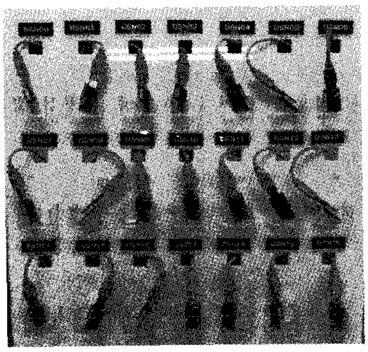

Fig. 1. An USN System with Kmote Units Which used for the Simulation Study.

Table 1. A Random Generated Sample of Active and Sleep Times (Unit: *msec*)

MAC \ Node		A	B	C	D	E
802.11	Active times	*12.0, 12.0, 12.0, 12.0, 12.0*	*12.0, 12.0, 12.0, 12.0, 12.0*	*12.0, 12.0, 12.0, 12.0, 12.0*	*12.0, 12.0, 12.0, 12.0, 12.0*	*12.0, 12.0, 12.0, 12.0, 12.0*
	Sleep times	*20.0, 20.0, 20.0, 20.0, 20.0*	*20.0, 20.0, 20.0, 20.0, 20.0*	*20.0, 20.0, 20.0, 20.0, 20.0*	*20.0, 20.0, 20.0, 20.0, 20.0*	*20.0, 20.0, 20.0, 20.0, 20.0*
S-MAC	Active times	*3.1, 1.2, 4.5, 2.1, 1.2*	*2.3, 2.1, 1.7, 1.5, 3.4*	*2.7, 3.6, 5.1, 3.2, 1,7*	*6.7, 2.9, 3.7, 2.8, 4.5*	*1.7, 3.2, 4.2, 2.8, 4.1*
	Sleep times	*28.9, 31.8, 27.5, 29.9, 31.8*	*29.7, 29.9, 30.3, 31.5, 28.6*	*29.3, 28.4, 27.9, 28.6, 30.3*	*25.3, 29.1, 28.3, 29.2, 27.5*	*30.3, 28.8, 27.8, 29.2, 27.9*
DS-MAC	Active times	*8.1, 10.3, 9.2, 7.5, 12.0*	*10.3, 4.2, 7.7, 9.5, 11.6*	*8.5, 10.0, 10.2, 11.3, 9.7*	*9.0, 7.8, 10.5, 9.4, 7.8*	*6.8, 7.5, 4.9, 6.9, 9.7*
	Sleep times	*13.9, 11.7, 12.8, 14.5, 10.0*	*11.7, 17.8, 14.3, 12.5, 10.4*	*14.6, 13.5, 12.0, 11.8, 12.3*	*13.0, 14.2, 11.5, 12.6, 14.2*	*15.2, 14.5, 17.1, 15.1, 12.3*
T-MAC	Active times	*1.2, 2.3; 0.9, 0.7, 1.3*	*0.7, 2.1, 1.6, 0.8, 1.5*	*2.1, 1.4, 0.7, 1.2, 1.8*	*0.9, 1.7, 1.9, 2.0, 1.3*	*1.5, 1.8, 0.7, 1.9, 2.4*
	Sleep times	*30.8, 29.7, 31.1, 31.3, 30.7*	*31.3, 29.9, 30.4, 31.2, 30.5*	*29.9, 30.6, 31.3, 30.8, 30.2*	*31.1, 30.3, 30.1, 30.0, 31.7*	*30.5, 30.2, 31.3, 30.1, 29.6*

units) under the USN system as shown in Figure 1 according to the contention-based slotted MAC protocols assuming that duty cycles (slots/frames) k_i=5, MTBA=12 *msec*, and MTBS=20 *msec*.

With theses generated sample, we calculate Bayes estimates of the system effectiveness in energy saving according to parameters of non-informative prior knowledge a_i= 1(2)5, b_i= 1(2)5, c_i = 1(2)3, d_i=1(2)3, duty cycles k_i=5, message interval=0.1(0.2)0.9, MTBA=12 *msec* and MTBS=20 *msec*. And we compare the Bayes estimates of system energy saving effectiveness under the non-informative prior knowledge and selected slotted contention-based energy efficient MAC protocols in Table 2 for 802.11 MAC, Table 3 for S-MAC, Table 4 for DS-MAC, and Table 5 for T-MAC, respectively.

Table 2. Bayes Estimates of the System Effectiveness in Energy Saving for 802.11 MAC in the Case of Non-informative Prior Knowledge

(u_i, v_i)	Message Interval				
	0.1	0.3	0.5	0.7	0.9
(1,1)	*0.625*	*0.625*	*0.625*	*0.625*	*0.625*
(1,3)	*0.627*	*0.627*	*0.627*	*0.627*	*0.627*
(1,5)	*0.629*	*0.629*	*0.629*	*0.629*	*0.629*
(3,1)	*0.627*	*0.627*	*0.627*	*0.627*	*0.627*
(3,3)	*0.632*	*0.632*	*0.632*	*0.632*	*0.632*
(3,5)	*0.637*	*0.637*	*0.637*	*0.637*	*0.637*
(5,1)	*0.632*	*0.632*	*0.632*	*0.632*	*0.632*
(5,3)	*0.637*	*0.637*	*0.637*	*0.637*	*0.637*
(5,5)	*0.639*	*0.639*	*0.639*	*0.639*	*0.639*

Table 3. Bayes Estimates of the System Effectiveness in Energy Saving for S-MAC in the Case of Non-informative Prior Knowledge

(u_i, v_i)	Message Interval				
	0.1	0.3	0.5	0.7	0.9
(1,1)	*0.901*	*0.894*	*0.860*	*0.824*	*0.805*
(1,3)	*0.906*	*0.896*	*0.862*	*0.826*	*0.807*
(1,5)	*0.908*	*0.898*	*0.867*	*0.828*	*0.809*
(3,1)	*0.906*	*0.896*	*0.862*	*0.826*	*0.807*
(3,3)	*0.901*	*0.891*	*0.867*	*0.831*	*0.812*
(3,5)	*0.906*	*0.896*	*0.877*	*0.836*	*0.817*
(5,1)	*0.901*	*0.901*	*0.867*	*0.831*	*0.812*
(5,3)	*0.906*	*0.906*	*0.877*	*0.836*	*0.817*
(5,5)	*0.908*	*0.907*	*0.883*	*0.838*	*0.819*

Table 4. Bayes Estimates of the System Effectiveness in Energy Saving for DS-MAC in the Case of Non-informative Prior Information

(u_i, v_i)	Message Interval				
	0.1	0.3	0.5	0.7	0.9
(1,1)	*0.852*	*0.825*	*0.795*	*0.775*	*0.725*
(1,3)	*0.857*	*0.827*	*0.797*	*0.777*	*0.727*
(1,5)	*0.859*	*0.829*	*0.799*	*0.779*	*0.729*
(3,1)	*0.857*	*0.827*	*0.797*	*0.777*	*0.727*
(3,3)	*0.852*	*0.832*	*0.802*	*0.782*	*0.732*
(3,5)	*0.857*	*0.837*	*0.807*	*0.787*	*0.737*
(5,1)	*0.852*	*0.832*	*0.802*	*0.782*	*0.732*
(5,3)	*0.857*	*0.837*	*0.807*	*0.787*	*0.737*
(5,5)	*0.859*	*0.839*	*0.809*	*0.789*	*0.739*

Table 5. Bayes Estimates of the System Effectiveness in Energy Saving for T-MAC in the Case of Non-informative Prior Information

(u_i, v_i)	Message Interval				
	0.1	0.3	0.5	0.7	0.9
(1,1)	*0.940*	*0.924*	*0.898*	*0.874*	*0.845*
(1,3)	*0.945*	*0.926*	*0.902*	*0.876*	*0.847*
(1,5)	*0.947*	*0.928*	*0.906*	*0.878*	*0.849*
(3,1)	*0.945*	*0.926*	*0.902*	*0.876*	*0.847*
(3,3)	*0.940*	*0.928*	*0.906*	*0.881*	*0.852*
(3,5)	*0.945*	*0.936*	*0.913*	*0.886*	*0.857*
(5,1)	*0.940*	*0.931*	*0.906*	*0.881*	*0.852*
(5,3)	*0.945*	*0.936*	*0.913*	*0.886*	*0.857*
(5,5)	*0.947*	*0.937*	*0.923*	*0.888*	*0.859*

From Table 2-5 for the comparison of the Bayes estimates of the system energy saving effectiveness in the case of non-informative prior knowledge, we have the following results:

(1) The proposed Bayes estimators are robust and stable in utilization as a performance evaluation tool for the system energy saving effectiveness in a wireless sensor network according to the values of non-informative prior knowledge with the parameters (u_i, v_i). The result of comparison of the system energy saving effectiveness is represented as T-MAC ≫S-MAC ≫DS-MAC ≫802.11 MAC, if we define "A ≫B" as that A is more effective than B, for (u_i, v_i)=1(2)5, duty cycles (slots/frames) $k_i = 5$, message interval = 0.1(0.2)0.9, MTBA=12 *msec* and MTBS=20 *msec*.

(2) When message interval increases from 0.1 to 0.9, the system energy saving effectiveness decreases for all values of prior knowledge parameters as we expected.

6. CONCLUSION

The wireless sensor network (WSN) sensor nodes operate on battery power which is often deployed in a rough physical environment as some networks many consists of hundreds to thousands of nodes to monitor, track, and control many civilian application areas such as environment and habitat monitoring, object tracking, healthcare, fire detection, traffic management, home automation, and so on.

The WSN medium access control (MAC) protocols are usually classified in two different groups: TDMA protocols (LMAC, TRAMA, PEDAMACS, and so on) and CSMA (carrier senses multiple accesses)-based protocols (S-MAC, T-MAC, B-MAC, DS-MAC, D-MAC, and so on). In WSN sensor nodes, MAC synchronizes the channel access in an environment where numerous sensor nodes access a shared communication medium. 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 and routing methods.

In this paper, we propose the Bayes estimators of the system energy saving effectiveness for a wireless sensor network system consisting of N non-identical deployed sensor nodes under the energy efficient CSMA contention-based MAC protocols such as S-MAC, DS-MAC and T-MAC based on IEEE 802.11.

In the case study, we have calculated these Bayes estimates for the system energy saving effectiveness of the WSNs according to the values of parameters of non-informative prior information after generation of exponential random variates and active and sleep times of the deployed sensor nodes from assumed MTBA and MTBS. And we have compared the system effectiveness in energy saving according to the slotted contention-based energy efficient MAC protocols such as 802.11, S-MAC, DS-MAC, and T-MAC. And we have also recognized that the proposed Bayesian system energy saving effectiveness estimation tools are excellent to adapt in evaluation of energy efficient contention-based MAC protocols using non-informative prior knowledge from previous experience as the case of conjugate prior information, and that it was difficult to assess energy efficiency of MAC protocols uniformly and generally due to the variety of experimental conditions such as kinds of motes, batteries, packet sizes, network topologies, and deployed distances of sensor nodes, and so on.

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