http://ansinet.com/itj

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (2): 264-275, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.264.275

Hybrid Traffic Oriented Energy Efficiency Access Strategy of Wireless Sensor Network

Yasong Wang, Qinyu Zhang and Yunhe Li
Department of Electronic and Information Engineering,
Harbin Institute of Technology, Shenzhen Graduate School, Shenzhen, China

Abstract: Under the hybrid background of both real-time and non-real-time traffics, this research studied the adaptive listening/sleeping mechanism of dynamic access of wireless sensor network nodes. The network nodes delivering non-real-time traffic, could switch status among transmitting state, listening state and sleeping state. On one hand, the energy consumption of network nodes is very low during sleeping state which could reduce the average energy consumption of network nodes effectively; on the other hand, overlong sleeping time might cause transmission opportunity missing. Therefore, according to the traffic condition of channels, setting reasonable sleeping overtime of Wireless Sensor Network (WSN) nodes could balance the tradeoff between energy consumption and transmission efficiency, so as to maximize WSN energy transmission efficiency. In this study, the problem is modeled by continuous-time Markov theory. Then, the system model is analyzed based on perturbation analysis technique. To find the optimal sleeping time that maximizes the energy efficiency, a gradient algorithm is presented. Last, the feasibility of the proposed method is verified by the comparison of theoretical result and computer simulation.

Key words: Wireless sensor network, hybrid traffic, energy efficiency, transmission efficiency, optimal sleeping time

INTRODUCTION

In recent years, the fast development of Wireless Sensor Network (WSN) has attracted the attention of both academic and industrial circles. Comprised of sensor nodes deployed in a specific geographical area, a typical WSN is mainly used to monitor physical phenomena, such as temperature, humidity, fire and earthquake. Generally, a WSN node consists of 3 parts: a sense subsystem, capturing change information of the external environment; an information processing subsystem, processing and storing local data and a communication subsystem, transmitting and receiving data. Besides, WSN nodes also need a power source to provide energy for the operation of equipment. The power source is usually a limited power supply battery. Since WSN is often deployed in severe geographical locations or hostile environment, it’s very difficult to recharge the battery. However, most of the applications require WSN has a long enough life cycle (day, month, etc.). Thus, under the condition of limited energy, how to prolong the life cycle as long as possible has become a key problem in WSN design (Akyildiz *et al*., 2002).

According to different network structures and application requirements, WSN can be classified into 2 types: duty-cycling network and event-driven network (Anastasi *et al*., 2009). Duty-cycling network is mainly used to implement Non-Real-Time (NRT) environment monitoring, such as weather monitoring and geographical location information collection, etc. (Ganesan *et al*., 2004); while even-driven network is mainly utilized to implement Real-Time (RT) environment monitoring, such as anti-terrorism security, intrusion prevention, disaster monitoring and equipment monitoring, etc. (Ye *et al*., 2002). Due to different application requirements, the research methods of energy efficiency are different. For duty-cycling network, the most effective means of improving energy efficiency is to set the sensor node in low powered sleeping state, when there’s no communication requirement. Ideally, sensor nodes could switch into sleeping state immediately when no data is transmitting and switch into communication state immediately when there is data transmitting. However, in practical system design, a node in sleeping state is usually assumed not to receive data and switching state could lead to a certain delay and energy consumption. Therefore, how to effectively schedule the switch of sleeping/communication state has become a major research interest in the energy conservation of duty-cycling network. The typical protocol is

---

Corresponding Author: Qinyu Zhang, Department of Electronic and Information Engineering,
Harbin Institute of Technology, Shenzhen, Graduate School, Shenzhen, China

Sensor-MAC (Ye *et al*., 2002; Ye *et al*., 2004) which utilizes virtual cluster as the unit period to synchronize sleep, prolongs the sleeping time of nodes and reduces node energy consumption. Much work is based on this protocol, such as Timeout-MAC (Van Dam and Langendoen, 2003) also utilizes sleep mechanism, although Timeout-MAC maintains a fixed period, yet the listening time could be adjusted according to the channel condition and the sleeping time could also be changed; Pattern-MAC (Tang *et al*., 2011) could adaptively adjust sleeping time according to network flow information; aiming at the sleep delay in Sensor-MAC, Latency-MAC (Wang and Liu, 2007) proposes a communication state of data aggregating in tree structure and could adjust sleeping time according to the tree structure. Latency-MAC needs to implement cluster-based synchronization periodically and the extra node energy consumption caused by synchronization could not be ignored, thus this method is limited in energy conservation. Considering the consumption of period synchronization, the second method is asynchronous access mechanism which only needs relatively short listening time to discriminate whether data needs receiving. El-Hoiydi (2002), Hill and Culler (2002), Mahlknecht and Bock (2004) and Buettner *et al*. (2006) asynchronously accessed channels to reduce idle listen via., prolonging the preamble of data frames. The advantage of this access method lied in when data is transmitting, only the transceiving nodes need synchronous channel and the other nodes avoid overhead caused by period synchronization; while the disadvantage is that the transmitting nodes have to maintain in listening state until the receiving nodes wake up, so as to transmit data, thus the listening overhead and the waiting delay are increased (Chang *et al*., 2008).

Comparatively, event-driven network has higher requirement for RT (Real-Time) data transmission, thus nodes have to keep in sense state, to make sure WSN nodes could transmit data to node Sink timely whenever emergency situation occurs. Therefore, event-driven network has higher priority. Researches have shown that a way to improve event-driven network energy efficiency is to decrease the size of the sample data, via the efficient data capture. Alippi *et al*. (2007) utilized the space-time correlation between data and adaptive sampling technology and reduced the sample size. Jain and Chang (2004) employed Kalman filter to obtain sampling rate. Willett *et al*. (2004) proposed an inversion algorithm which could acquire enough precise description of status information through a certain sample size, based on the space-time correlation of sense information. Kijewski-Correa *et al*. (2006) applied the trigger sampling state to medical monitoring and injury detection. Another way to increase the energy efficiency of event-driven network is data prediction. Through mathematical modeling to describe the phenomenon sensed, queries could be answered using the model instead of the actually sensed data. Tulone and Madden, 2006 proposed PAQ (Probabilistic Adaptable Query) system based on time series forecasting which used low order AR model and effectively decreased the calculation amount of network nodes. Borgne *et al*. (2007) extended the time series forecasting method with adaptive multi-model selection mechanism. The main idea is that when the prior knowledge of an environmental state couldn’t be acquired, the system itself could automatically select a correct model to predict the environment.

Although the existing researches have studied the energy conservation problem of duty-cycling and event-driven networks, yet there’s still few research on the network of hybrid traffic. The deployment of both duty-cycling and event-driven networks could enhance the environmental adaptation ability of WSN and meet more extensive application requirements. In this article, WSN in hybrid network state would be modeled and the sleep mechanism is studied, with emphasis on duty-cycling network. The nodes of duty-cycling network are mainly used for the NRT traffics which have lower requirement of transmission delay, such as environmental routine test, etc. and could switch states among transmission, sleeping and listening; the nodes of event-driven network are mainly utilized for RT data traffics which are sensitive to data transmission delay, such as emergent environmental events and maintain in listening or communication state and RT traffics have higher priority of channels. How to improve the energy efficiency of RT traffic is not within the research interests of this article. More information about it could refer to Sazak *et al*. (2010) and Zhou *et al*. (2008). This article studies the optimal sleeping time of NRT (Non-Real-Time) traffic under the hybrid network of both RT and NRT traffics, in order to maximize the energy efficiency of network nodes.

SYSTEM MODEL

Figure 1 is a schematic diagram of hybrid WSN of both RT and NRT traffics. The states of sensor nodes are sleep, listening and communication states. Figure 1a presents the states snapshot of nodes. When node A needs to transmit NRT data to node Sink, the routing protocol determines the transmission route first, then node A transmits data along this route. During this process, nodes of this transmission route are in transceiving state after wake-up and the other nodes

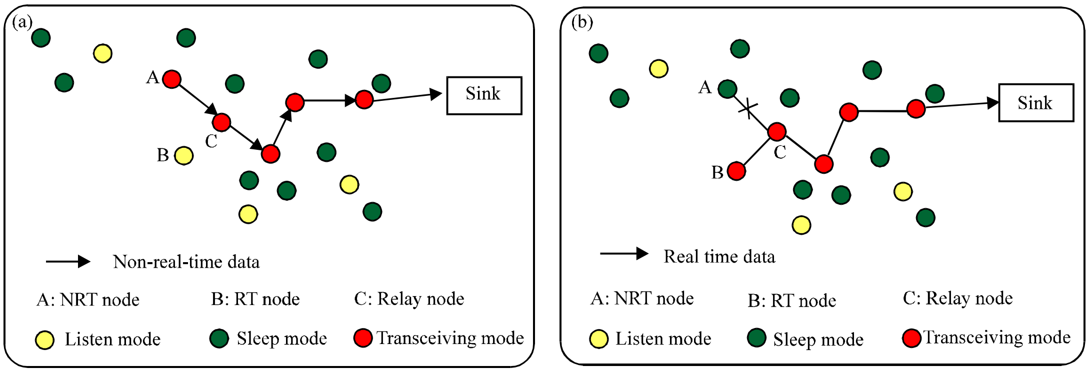

Fig. 1(a-b): Transmission schematic diagram of (a) NRT and (b) RT traffic

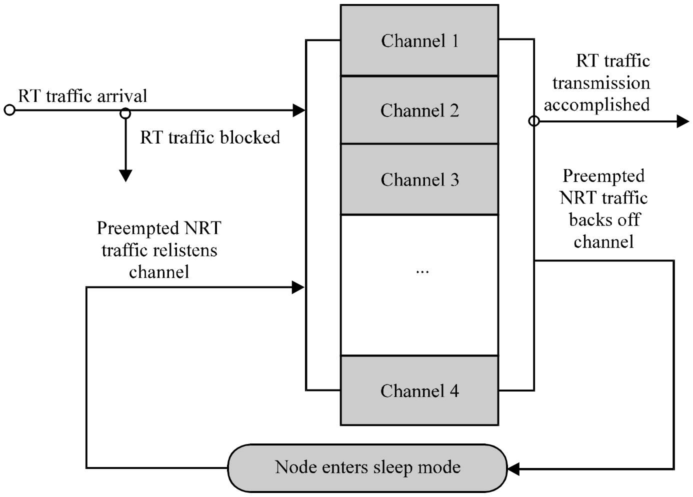

Fig. 2: Hybrid traffic access model of WSN

maintain their sleeping/listening time. When RT traffic needs to be transmitted to node Sink, since RT traffic has higher priority, NRT traffic would back off the channel that could influence the transmission of RT traffic. As shown in Fig. 1b, when node B needs to transmit RT traffic to node Sink and node C serves as a relay node, under this circumstance, node A suspends the transmission of NRT traffic and enters sleeping state and node B gets the channel access to transmit.

Node state transition model based on Markov: In a limited area, WSN has N available channels, RT nodes and NRT nodes. Figure 2 presents the schematic diagram of channel access, where an RT node has the absolute priority of channel access, i.e., it could randomly get access to the channels which are not occupied by other RT nodes. Only when all the channels are occupied by RT nodes, will the new arrival RT traffic be blocked. To ensure the prior transmission of RT data, the transmission of NRT data could occasionally use the channels which are not occupied by RT data. When the channel is preempted by RT data, NRT data will back off the transmission channel and wait for the next access.

Assuming that the total number of NRT nodes in three states are M; the arrival time interval of RT data traffic obeyed Poisson's distribution with the parameter of λ_{RT}; the transmission time of RT and NRT in channels obeyed negative exponential distribution with parameter of t_{RT} and t_{NRT}, respectively. The average listening time and the sleeping time of network nodes of NRT data were t_t and t_s, respectively.

The above access process can be modeled by a 4-dimension continuous-time Markov chain. Define a 4-dimension vector a: = (i, j, k, l) to express the state of WSN at each moment, where i, j represents the number of nodes which are transmitting RT and NRT traffics, respectively. k, l represents the number of NRT nodes in listening state and sleeping state, respectively. The state space is:

$$\Omega = \{a: = (i, j, k, l) | 0 \leq i+j \leq N, j+k+l = M\}$$

The size of the state space $|\Omega| = A$. Without loss of generality, assuming the current state of system is (i, j, k, l), according to the previous description, the state transitions probably may occur are as below:

When there are idle channels, i.e., $i+j<N$, NRT nodes might be in two states-transmitting or sleeping state. At this moment, the relationships among parameters are $I+j<N$, $k = 0$, $j+l = M$. The state transition of the system had five possibilities as follows:

- A node has RT data to transmit and accesses channel through competition, then the system state would transfer to (I+1, j, 0, l) with rate $(N\text{-}i\text{-}j/N\text{-}i)\ \lambda_{RT}$
- RT traffic arrives at system first and preempts the channel of NRT traffic, the preempted NRT node turns into sleeping state quickly, the system state would transfer to (I+1, j-1, 0, l+1) with rate $(j/N\text{-}1)\ \lambda_{RT}$
- RT traffic is accomplished and exited from the channel, the system state would transfer to (I-1, j, 0, l) with rate i/t_{RT}
- NRT traffic is accomplished, it would exit from the channel and turn into sleeping state, the system state would transfer to (i, j-1, 0, l+1) with rate j/t_{NRT}
- If the sleep of a node ended and there are idle channels, the node would turn into listening state first and get access to channel immediately, the system state would transfer to (i, j+1, 0, l-1) with rate l/t_s

The transition model is shown in Fig. 3.

When channels are all busy and there are NRT nodes in listening state, i.e., $I+j = N$, $k \neq 0$, then the relationships among parameters are: $i+j = N$, $k \neq 0$, $j+k+l = M$. The state transition of the system has the following five possibilities:

- RT traffic arrives first and has to preempt the channel of NRT traffic, the network node preempts turned into sleeping state, the system state would transfer to (I+1, j-1, k, l+1), with rate λ_{RT}
- RT traffic is accomplished and exited from the channel. The node in listening state would get access to the channel immediately and the access is in accordance with FIFO (first-in-first-out) rule, the system state would transfer to (I-1, j+1, k-1, l) with rate i/t_{RT}
- NRT traffic is accomplished, it would exit from the channel and turn into sleeping state. The node in listening state would get access to the channel immediately, the system state would transfer to (i, j, k-1, l+1) with rate j/t_{NRT}
- The network node in listening state is overtime. Since there still no idle channel the node is shifted into sleeping state, the system state would transfer to (i, j, k-1, l+1) with rate k/t_t. Since the third and fourth possibilities had the same state transition, thus they are classified into one process with rate $k/t_t+j/t_{NRT}$
- The node in sleeping state is overtime. Since, there still no idle channel, the node would turn into listening state and listen channels, the system state would transfer to (I, j, k+1, l-1) with rate l/t_s

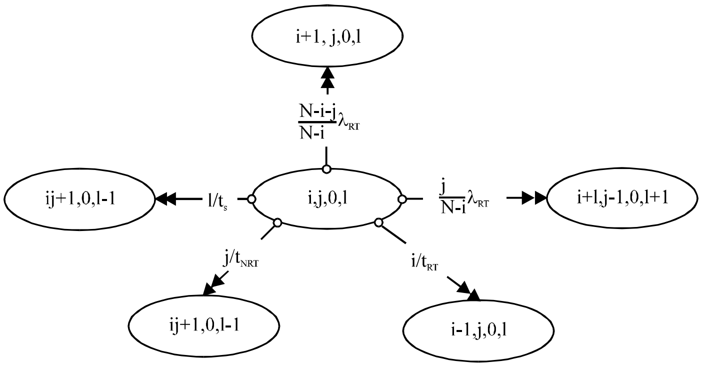

Fig. 3: System transition rate diagram when channels are not busy, i, j, 0, l: Current system state, N: No. of wireless channels, λ_{RT}: Arrival rate of RT traffic, t_{RT} and t_{NRT}: Average service time of RT and NRT traffic, respectively, t_s: Average sleeping time of network nodes

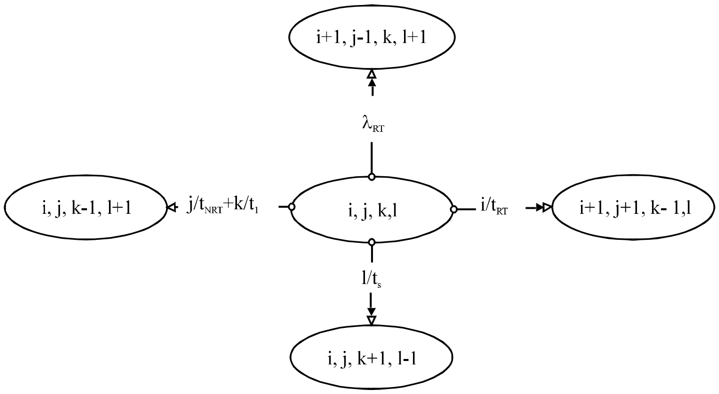

Fig. 4: System transition rate diagram when channels are busy and there are NRT nodes in listening state, i, j, k, l: Current system state, λ_{RT}: Arrival rate of RT traffic and λ_{RT}: Average service time of RT and NRT traffic, respectively, t_s and t_l: Average sleeping time and listening time of network nodes, respectively

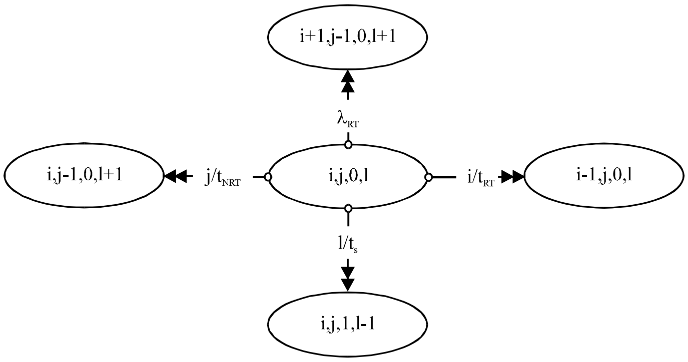

Fig. 5: System transition rate diagram when channels are busy and there is no NRT node in listening state, i, j, k, l: Current system state, λ_{RT}: Arrival rate of RT traffic, t_{RT} and t_{NRT}: Average service time of RT and NRT traffic, respectively, t_s and t_l: Average sleeping time and listening time of network nodes, respectively

The transition model is shown in Fig. 4.

When channels are all busy and there is no NRT node in listening state, i.e., $i+j = N$, $k = 0$, the relationships among parameters are: $i+j = N$, $k = 0$, $j+l = M$. The state transition of the system has the following five possibilities:

- RT traffic arrived and preempts NRT channel, the preempted node would shift into sleeping state. The system state would transfer to (i+l, j-1, 0, l+1) with rate λ_{RT}
- RT traffic is accomplished and exited from the channel. Since, there is no node in listening state, the system state would transfer to (i-1, j, 0, l) with rate i/t_{RT}
- NRT traffic is accomplished and exited from the channel. The node would turn into sleeping state and the system state would transfer to (i, j-1, 0, l+1) with rate j/t_{NRT}
- The node in sleeping state is overtime. Since channels are not idle, the node would shift into listening state and listen channels and the state would transfer to (i, j, 1, l-1) with rate l/t_s

The transition model is shown in Fig. 5.

PERFORMANCE EVALUATION

Steady-state probability: The steady-state probability of each system state can be solved using the steady-state property of continuous-time Markov chain. According to the above modeling process, the steady-state probability corresponding to the state in state space Ω is $\pi = \{\pi_S = \pi_{i,j,k,l} | 0 \leq i+j \leq N, j+k+l = M\}$. Define Markov process state transition rate matrix as Q and assuming s is the current state, s' is the next state, matrix Q could be expressed as:

$$Q_{a,a'}\big|_{s=(i,j,k,l),s'=\Omega}=\begin{cases}\frac{N-i-j}{N-i}\lambda_{RT} & a'=(i+1,j,k,l)\\ \frac{j}{N-i}\lambda_{RT} & a'=(i+1,j-1,k,l+1)\\ l/t_s & a'=(i,j+1,k,l-1)\\ i/t_{RT} & a'=(i-1,j,k,l)\\ j/t_{NRT}+k/t_1 & a'=(i,j,k-1,l+1)\\ j/t_{NRT} & a'=(i,j-1,k,l+1)\\ Q_{s,s}=-\sum_{s\neq s'}Q_{s,s'} & \\ 0 & \text{others}\end{cases}\tag{1}$$

The first column of matric Q is replaced by e, the unit column matric and $\pi e = 1$, Q is changed into Q_1, since $\pi Q = 0$, let $b = [1\ 0\ 0\ ...]$, then $\pi = bQ_1^{-1}$ and then $\pi = bQ_1^{-1}$, i.e., the solution of π is the first row of Q_1^{-1}.

QoS analysis: All the three system states consume energy. Assuming the energy consumptions in unit time under transmitting, listening and sleeping states are E_t, E_l and E_S, respectively, where the energy consumption E_t of communication state is the largest, the consumption E_l of listen state is the second largest and the consumption E_d of sleeping state is the least, i.e., $E_t > E_l > E_S$. Additionally, considering reducing the interference of NRT traffic to RT traffic, the constraint of collision probability of these two traffics is required. The parameter indexes in this article are as follows:

Transmission time (T_t): It defined as the total transmission time of NRT traffic in channels. NRT traffic only transmits in the channels which had no RT traffic. Assuming the simulation time is T_{simu}, according to the above description, the state $a = (i, j, k, l)\epsilon\Omega$ of the state space are analyzed and assuming the node transmission time per unit data is τ, then the total transmission time of NRT traffic under that state is:

$$T_t^a = j\times\tau \tag{2}$$

The average quantity transmitted per unit time is denoted by:

$$n_t=\frac{T_t^a}{T_{simu}}=\frac{j\times\tau}{T_{simu}}$$

According, to the physical significance of steady-state probability, the steady-state probability of the current state $\pi_S = \tau/T_{simu}$, $n_t = j_a\times\pi_a$ could be obtained. Therefore, the total transmission time in state space is:

$$T_t = \Sigma_{a\epsilon\Omega} j\pi_a \tag{3}$$

Listening time (T_l): It defined as the total time of nodes in listening state. According to the above-mentioned derivation method, valid state $a = (i, j, k, l)\epsilon\Omega$, listening time $T_d^a = k\times\tau$ and the total listening time of nodes is:

$$T_l = \Sigma_{a\epsilon\Omega} k\times\pi_a \tag{4}$$

Sleeping time (T_S): It defined as the total sleeping time of nodes in sleeping state. Also according to the above derivation method, valid state $(i_a, j_a, k_a, l_a)\epsilon\Omega$, sleeping time $T_d^a = l_a\times\tau_a$ and the total sleeping time of nodes is:

$$T_S = \Sigma_{a\epsilon\Omega} l\times\pi_a \tag{5}$$

Transmission efficiency (η^t): It defined as the bit transmission traffic per unit time. The transmission time of DCN in state space is:

$$T_a^t = j\times\pi_a \tag{6}$$

The total transmission efficiency of the system is:

$$\eta^t = T_a^t/T_{simu} = j_a\times\pi_a/T_{simu} \tag{7}$$

Energy efficiency (η_e): It defined as the bit number of transmitted data per unit energy consumed in NRT traffic. Thus, energy efficiency is the ratio of average transmission bit number per unit time to average consumed energy per unit time:

$$\eta_e=\frac{\text{Average transmission bit number per unit time}}{\text{Average consumed energy per unit time}} \tag{8}$$

The total consumed energy is $E = n_t\times E_t + n_S\times E_S + n_d\times E_d$ and the energy efficiency is:

$$\eta_a=\frac{j_a\times\pi_a}{E}=\frac{j_a*\pi}{j_a\times\pi_a\times E_t+k_a\times\pi_a\times E_s+l_a\times\pi_a\times E_d}=\frac{j_a}{j_a\times E_t+k_a\times E_s+l_a\times E_d} \tag{9}$$

The total energy efficiency of the system is:

$$\eta=\sum_{a=1}^{s}\eta_a=\sum_{a=1}^{s}\frac{j_a}{j_a\times E_t+k_a\times E_s+l_a\times E_d} \tag{10}$$

Collision probability ($P_{collision}$) of RT traffic and NRT traffic: When channels are busy with RT traffic, the RT traffic arrived at next moment would be blocked; P_{block} represented the blocking rate of RT traffic and is expressed as:

$$P_{block} = \sum_{k=0}^{M} \sum_{l=0}^{M-k} \pi_{N,0,k,l} \tag{11}$$

The collision probability of RT traffic and NRT traffic is under the precondition that RT traffic is not blocked, the new arrival RT traffic occupies the channel that NRT traffic is transmitting and $P_{collision}$ represents the collision probability and is expressed as:

$$P^{a}_{collision} = \sum\nolimits_{a\in\Omega} \pi_a \frac{\frac{j}{N-i}}{1-P_{block}} = \sum\nolimits_{a\in\Omega} \pi_a \frac{\frac{j}{N-i}}{1-\sum\limits_{k=0}^{M}\sum\limits_{l=0}^{M-k}\pi_{N,0,k,l}} \tag{12}$$

This study, assumed the upper limit of collision probability is $P_{collision\text{-}threhold}$, aiming at under the precondition that collision probability dose not exceed the upper limit, i.e., $P_{collision} \le P_{collision\text{-}threhold}$, solving the optimal sleeping time of NRT traffic in WSN which could maximize energy efficiency η.

SOLUTION OF OPTIMAL SLEEPING TIME BASED ON PA

Stochastic dynamic system: Stochastic dynamic system is a dynamic system subjected to the evolution of time and the optimization problem of the system is to obtain the output of history based on the observed and input history, determine the action to optimize the total reward of the system in each sample space and find the corresponding optimal strategy. When the number of strategies is limited, the optimal strategies always exist and may be not only one. Assuming at any moment $l = 0, 1, 2...$, the system state is denoted by S_l, $l = 0, 1,...$, the sample path of state space is the record of state history and denoted by $S = \{S_0, S_1, S_2,...\}$, S_l is a stochastic variable, the sample path expressed the dynamic action of the system. For each sample path H_l, $l = 0, 1,..., L$, there is a reward and denoted by $\eta_l (H_l)$. When the length of the sample path is limited and denoted by L, $\eta_L (H_L)$ represented all the rewards of ergodic sample paths and the system performance metric is defined as the limit of average reward:

$$\eta = \lim_{L\to\infty} E[\eta_L(H_L)]$$

where, the existence of both expectation and limit are assumed.

In the optimization problem of Markov model, reward function existed and is denoted by $f(i, \alpha)$, $i\in S$, $\alpha\in A$ which represented the reward $f(i, \alpha)$ gained by the system in state i at moment l, by taking action α. For the limited sample path with the length of L, the total reward of the system is:

$$\eta_L = \sum_{l=0}^{L-1} f(X_l, A_l)$$

and the performance metric is:

$$\eta = \frac{1}{L}\sum_{l=0}^{L-1} f(X_l, A_l)$$

For the ergodic Markov chain, the long-term average reward is:

$$\eta = \lim_{L\to\infty}\frac{1}{L}\sum_{l=0}^{L-1} f(X_l, A_l)$$

which is independent of initial state.

There are many methods about the modeling analysis and optimization strategy of stochastic dynamic system. Tlelo-Cuautle *et al.* (2010) discussed thoroughly the state of the art in applying evolution algorithm to solve practical considerations. Based on this, Polanco-Martagon *et al.* (2012) recently proposed a fuzzy sets intersection procedure to select the optimum sizes of analog circuits composed of Metal-Oxide semiconductor Field-Effect-Transistors (MOSFETs). Queuing network method and Markov Decision Processes (MDPs), PA, etc., (Cao and Chen, 1997) are also effective tools to solve specially uncertain system. Queuing network method is a traditional method based on queuing theory, that mainly focuses on the analysis of average steady-state statistic performance of network systems. MDPs are suitable for the modeling analysis of actual systems. With the complexity of system model and environment, such as the dimension of state space and the unknown system parameters, MDPs apparently cannot meet the requirements. For this problem, PA has a certain advantage over MDPs. PA is the core of learning and optimization method based on gradient (or strategy gradient). By analyzing a single sample path of a stochastic dynamic system, PA could estimate the derivative of performance with respect to the system parameter. The early work of PA focused on queuing system and then is extended to Markov system (Ho and Cao, 1994). Based on one sample path of Markov system, PA could estimate the performance derivatives of all directions. The derivatives could be estimated as a whole, without considering the performance potential of each state. This study utilized PA technique to estimate the system performance. For the mentioned system model, under the circumstance that the system parameter is certain, by changing the variable parameter t_s (strategy), the optimal strategy of system energy efficiency could be found using gradient algorithm.

Gradient algorithm based on PA technique: If only analyzing the system under one strategy, it is hard to know the action of system under other strategies. If two strategies are very "close", the system performances under these two strategies would also be similar. According to this, after the analysis of system performance under one strategy, the action could be "predict" and the system performance of the "close" strategy could be calculated (Vickers and Cannings, 1987). Assuming a strategy space could be expressed by continuous parameter, if two strategies are close correspondingly, this strategy space called continuous strategy space. In this article, the strategy referred to the average sleeping time, thus it is continuous-time strategy. The slight change of average sleeping time is in correspondence to the change of DCN average sleeping rate and the transition probability matrix would also change accordingly. Therefore, if DCN average sleeping time is close, the two strategies could be regard as close strategies. Then, the influence of slight change of average sleeping time on the system performance could be predicted by PA technique, then the derivative of system performance could be obtained and the performance gradient of each strategy in strategy space could also be acquired. Using the optimization algorithm of gradient, the local optimal point could be determined. The gradient algorithm structure based on PA is shown in Fig. 6.

Gradient based algorithm for optimal sleeping time: The WSNs transmitting hybrid traffic is moded as a continuous time Markov chain with state transition rate matrix Q, the state space Ω and the steady probability vector π. According to the Markov theory, Q and π satisfy the following equations:

$$\begin{cases} pe = 1 \\ Qe = 0 \\ pQ = 0 \end{cases} \tag{13}$$

According to Eq. 12, the collision probability in state a, denoted as f_a^p, can be obtained as:

$$f_p^a = P_{collision} = \frac{\dfrac{j_a}{N - i_a}}{1 - \sum_{k=0}^{M}\sum_{l=0}^{M-k} \pi_{N,0,k,l}},\ a \in \Omega \tag{14}$$

And According to Eq. 10, the energy efficiency in state a, denoted as f_a^c, can be obtained as:

$$f_c^a = \frac{j}{jE_t + kE_l + lE_s},\ a \in \Omega \tag{15}$$

Denote the collision probability vector and energy efficiency vector as f_p = $[f_1^p,\ f_2^p, \cdots f_A^p]$ and f_c = $[f_1^c,\ f_2^c, \cdots f_A^c]$, respectively. Therefore, these total performance measurement can be obtained as follows:

$$\eta_p = \lim_{T\to\infty} \frac{1}{T} E[\int_0^T f_p(X_t)dt] = pf_p \tag{16}$$

$$\eta_c = \lim_{T\to\infty} \frac{1}{T} E[\int_0^T f_c(X_t)dt] = pf_c \tag{17}$$

where, E is the expected operator. This study aim to get the optimal node sleeping time that maximizes the energy efficiency while satisfying the collision probability requirement. This can be formulated as an optimization problem as:

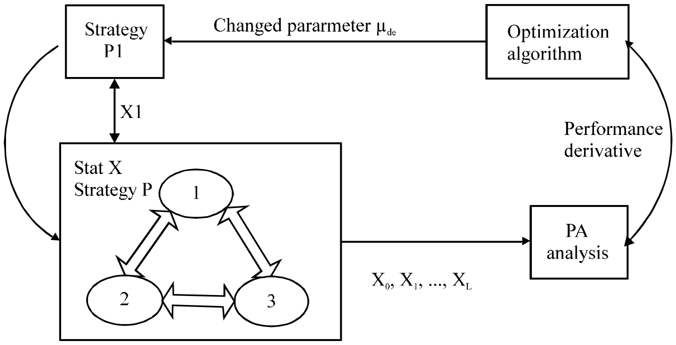

Fig. 6: Gradient algorithm based on PA technique

$$\begin{aligned} & t_s \in \operatorname{argmax} \eta_c \\ \text{s.t.} \quad & \eta_g \le P_{\text{collision-threhold}} \end{aligned} \tag{18}$$

To find the optimal solution to Eq. 18, a gradient based algorithm is presented. Define the performance potential performance potential of collision probability and energy efficiency in state a as follows (Cao and Chen, 1997):

$$g_p^a = E\left\{\sum_{l=0}^{\infty}\left[f_p(X_l) - \eta_p\right] \mid X_0 = a\right\} \tag{19}$$

$$g_c^a = E\left\{\sum_{l=0}^{\infty}\left[f_c(X_l) - \eta_c\right] \mid X_0 = a\right\} \tag{20}$$

The physical meaning of performance potential indicates the sum of the contribution in state a and that in the future possible states starting from state a. They satisfy the Poisson formulation:

$$(I-Q)g_p + \eta_p e = f_p \tag{21}$$

$$(I-Q)g_c + \eta_c e = f_p \tag{22}$$

where, I is identity matrix. By substituting Eq. 13 into 21 and 22 and differentiating t_s on the two sides of (21) and (22), get the gradient information of η_g and η_c with respect to t_s are:

$$\nabla \eta_p(t_s) = \sum_{i \in S} \pi_i(t_s) \sum_{j \in S} \nabla Q_{ij}(t_s) g_p^j(t_s) \tag{23}$$

$$\nabla \eta_c(t_s) = \sum_{i \in S} \pi_i(t_s) \sum_{j \in S} \nabla Q_{ij}(t_s) g_c^j(t_s) \tag{24}$$

Based on the gradient information in Eq. 23 and 24, a gradient based iteration algorithm is designed to find the optimal node sleeping time as follows:

Algorithm 1: Gradient based iteration algorithm

```
Step 1: Initialize the system parameters RT and NRT traffic arrival rate $\lambda_{RT}$ and $\lambda_{NRT}$, average service time $t_{RT}$ and $t_{NRT}$, average listening time $t_l$ and average sleeping time $t^k_s$, the number of channel N, the number of network nodes M, iteration times k = 0
Step 2: According to the initial parameter, set state transition matrix Q and solve the steady state probability $\pi$
Step 3: Substituting $t^k_s$ into (16) and (17) to get $\eta_p(t^k_s)$ and their gradient $\nabla\eta_p(t^k_s)$ and $\nabla\eta(t^k_s)$
Step 4: Renew Sleeping Time
if $\nabla\eta_c(t^k_s) > 10^{-4}$ or $\eta_g \ge P_{\text{collision-threhold}}$
renew sleeping time according to the following equation:
$t^{k+1}_s = (t^k_s + \kappa_k \nabla\eta_c)(t^k_s)) + (P_{\text{collision-threhold}} - \eta_p)\nabla\eta_p(t^k_s)$
where, $\kappa_k = \alpha_1 \times \alpha^k_2 + b$, $0<\alpha_1, \alpha_2<1$, $b>0$ is step adjustment factor.
go to Step 3.
else
    Output the optimization sleeping time $t_s$
        $t_s \leftarrow (t^k_s)$
endif
```

SIMULATION RESULTS AND ANALYSIS

To verify the correctness and effectiveness of the proposed algorithm, a set of computer simulation is carried out. The simulation parameters are set as follows: N = 8, M = 10, λ_{RT} = [0.1,1], t_{RT} = 2, t_{NRT} = 5, $P_{\text{collision-threhold}}$ = 0.3, t_t = 0.1, E_t = 1, E_l = 0.5, E_S = 0.05. Considering the change regulation of each performance index in different sleeping time, assuming t_s changes from 1 to 10.

Transmitting time and listening time: Figure 7 and 8 show the variation of transmitting time and listening time of NRT traffic, respectively, with the variation of sleeping time t_s. It can be seen that there is tiny gap between simulation results and theoretical results which proves the correctness of the analysis method based on Markov theory.

As shown in Fig. 7, the transmitting time decreases with the increase of sleeping time t_s and the slope decreases as well. This is because the average sleeping time of NRT node increases with the growth of t_s, the

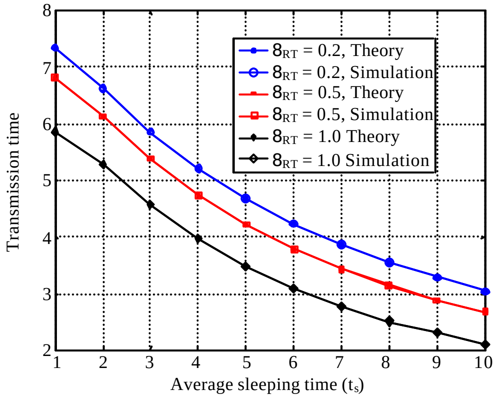

Fig. 7: Change of transmission time with sleeping time

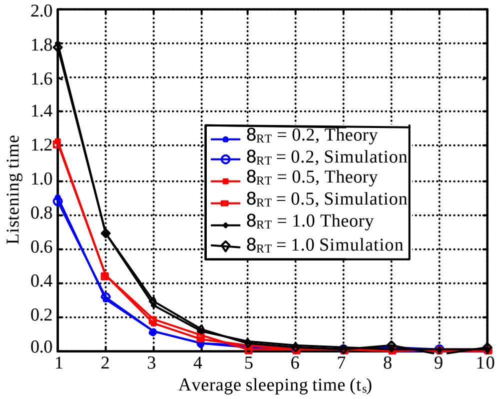

Fig. 8: Change of transmission with listening time

opportunity of finding idle channels declined, thus the transmission time decreases. But when t_s rises to a certain value, mores, the transmission time would approach to a certain value. Figure 7 also describes the change trend of transmitting time with the arrival rate λ_{RT} of RT traffic λ_{RT}. With the growth of λ_{RT}, the occupation of RT traffic to channels increased, thus at the same level of sleeping time, there are less transmitting opportunities for NRT traffic which results in the decreasing of the average transmission time.

Figure 8 shows the change of total listening time of NRT nodes with the variation of average sleeping time t_s. a. When t_s is small, the average duration between two consecutive sleeping period is short and the total listening time would increase under the precondition that RT traffic reached a certain arrival rate. Meanwhile, when the average sleeping time becomes relatively large, the transmission opportunities captured by NRT nodes would be decreasing which results that there are less NRT nodes transmitting over the network. Meanwhile, when the arrival rate λ_{RT} of RT traffic decreases, the transmission opportunities captured by nodes reduce, the increase of transmission time would slow down and nodes would be in listening state most of the time.

Energy efficiency: Figure 9 demonstrates the energy efficiency of NRT nodes in WSN. It is obvious that there is an optimal sleeping time making the energy efficiency of NRT nodes maximal. As discussed in previous section, we know that the energy consumption of NRT nodes includes transmitting state, listening state and sleeping. According to (10), we can know that more transmitting time will be benefit to energy efficiency, the transmitting time can be adjusted by changing sleeping time. However, as shown in Fig. 7 and 8, the increase of transmitting time means the more listening time which in turn increases the invalid energy consumption and decrease total energy efficiency. This is the reason why there is an optimal sleeping time for energy efficiency of NRT nodes. When t_s was relatively large, the system energy consumption was relatively small. When t_s was less than a certain range, although the system energy consumption increased with the decrease of average sleeping time, the transmission efficiency increased with fast growth and the energy efficiency increased gradually. But when the sleeping time kept on increasing, the channel capacity of the system tended to saturation, the growth trend of transmission time slowed down and the growth of system listening time speeded up, thus the system energy efficiency began to drop. Meanwhile, it can be seen that the traffic rate of RT nodes has significant impact on the upper bound of energy efficiency.

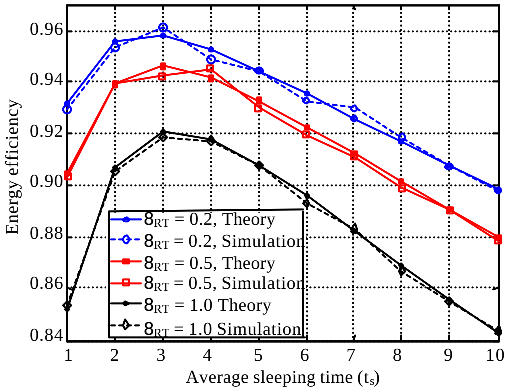

Fig. 9: Change of energy efficiency with sleep rate

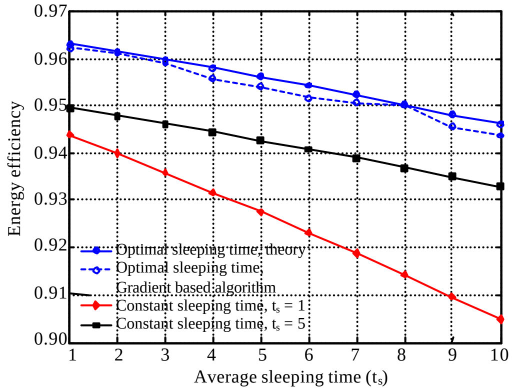

Fig. 10: Comparison among gradient algorithm, theoretical optimal solution and constant sleeping time

Performance of gradient algorithm: According to the result of Fig. 9, the change of energy efficiency with sleep rate is a convex function, or the change of t_s is a concave function. Therefore, we can exploit PA theory and proposed algorithm based on gradient to find the optimal sleeping time such that NRT nodes have the maximal energy efficiency. Fig. 10 presents the comparison result among gradient algorithm, theoretical optimal solution and constant sleeping time. As shown in Fig. 10, the gradient algorithm is very close to the theoretical optimal solution but more efficient than the solution method of optimal solution based on constant sleeping time method. Meanwhile, it could be seen that under the configuration of different system parameters, the energy efficiency of WSN could rise by 10% with optimized average sleeping time which means the proposed sleeping time optimization method can improve the lifetime of NRT nodes by 10% or more.

CONCLUSION

In this study, we present an energy-efficiency dynamic access mechanism for hybrid traffic WSN. By employing continuous-time Markov method, we formulate an optimization problem with objective function of energy efficiency, under the constraint of the collision probability of RT and NRT nodes. Based on the formulation, we derive the QoS index of NRT traffic including transmission time, listening time, transmission efficiency, energy efficiency collision probability () of RT traffic and NRT traffic and their relations with sleeping time. According the derived results, we conclude that all these QoS index can be adjusted by sleeping time and energy efficiency of NRT nodes is a convex function with respective to sleeping time. By using PA technique, we propose a gradient based algorithm to find the optima sleeping time. Simulation results indicate that the energy efficiency of NRT nodes can be improved by 10% or more via the proposed algorithm. Meanwhile, the optimal sleeping time varies with traffic strength of RT nodes. Future works will focus on the relationship between the optimal sleeping mechanism and network environment (like traffic strength of RT nodes, channel conditions, route protocol, etc.), to further improve the energy efficiency, as well as the lifetime of WSN.

ACKNOWLEDGMENTS

The study is sponsored by The National Basic Research Program of China (973 Program) (2009CB320402) and The National Natural Science Foundation of China (61001092).

REFERENCES

Akyildiz, I.F., W. Su, Y. Sankarasubramaniam and E. Cayirci, 2002. Wireless sensor networks: A survey. Comput. Networks, 38: 393-422.

Alippi, C., G. Anastasi, C. Galperti, F. Mancini and M. Roveri, 2007. Adaptive sampling for energy conservation in wireless sensor networks for snow monitoring applications. Proceedings of the IEEE International Conference on Mobile Adhoc and Sensor Systems, October 8-11, 2007, Pisa, pp: 1-6.

Anastasi, G., M. Conti, M. di Francesco and A. Passarella, 2009. Energy conservation in wireless sensor networks: A survey. Ad Hoc Networks, 7: 537-568.

Borgne, Y.A.L., S. Santini and G. Bontempi, 2007. Adaptive model selection for time series prediction in wireless sensor networks. Signal Process., 87: 3010-3020.

Buettner, M., G.V. Yee, E. Anderson and R. Han, 2006. X-MAC: A short preamble MAC protocol for duty-cycled wireless sensor networks. Proceedings of the 4th International Conference on Embedded Networked Sensor Systems, October 31-November 3, 2006, Boulder, Colorado, USA., pp: 430-430.

Cao, X.R. and H.F. Chen, 1997. Perturbation realization, potentials and sensitivity analysis of Markov processes. IEEE Trans. Autom. Control, 42: 1382-1393.

Chang, Y.C., J.R. Jiang, J.P. Sheu and H.Y. Shih, 2008. Adca: An asynchronous duty cycle adjustment mac protocol for wireless sensor networks. Proceedings of the Global Telecommunications Conference, IEEE GLOBECOM, November 30-December 4, 2008, New Orleans, LO., pp: 1-5.

El-Hoiydi, A., 2002. Aloha with preamble sampling for sporadic traffic in ad hoc wireless sensor networks. Proceedings of the IEEE International Conference on Communications, Volume 5, April 28-May 2, 2002, Centre Suisse Electronique et de Microtechnique SA., Neuchatel, pp: 3418-3423.

Ganesan, D., A. Cerpa, W. Ye, Y. Yu, J. Zhao and D. Estrin, 2004. Networking issues in wireless sensor networks. J. Parallel Distrib. Comput., 64: 799-814.

Hill, J.L. and D.E. Culler, 2002. Mica: A wireless platform for deeply embedded networks. IEEE Micro, 22: 12-24.

Ho, Y.C. and X. Cao, 1994. Realization Probabilities: The Dynamics of Queueing Systems. Springer-Verlag, New York, ISBN: 9783540198727.

Jain, A. and E.Y. Chang, 2004. Adaptive sampling for sensor networks. Proceedings of the 1st International Workshop on Data Management for Sensor Networks: In Conjunction with VLDB 2004, August 30, 2004, Toronto, Canada, pp: 10-16.

Kijewski-Correa, T., M. Haenggi and P. Antsaklis, 2006. Wireless sensor networks for structural health monitoring: A multi-scale approach. Proceedings of the 17th Analysis and Computation Specialty Conference on ASCE Structures Congress, May 18-21, 2006, St. Louis, MO., USA., pp: 1-16.

Mahlknecht, S. and M. Bock, 2004. CSMA-MPS: A minimum preamble sampling MAC protocol for low power wireless sensor networks. Proceedings of the IEEE International Workshop on Factory Communication Systems, September 22-24, 2004, Vienna University of Technology, Vienna, Austria, pp: 73-80.

Polanco-Martagon, S., G. Reyes-Salgado, G. Flores-Becerra, I. Guerra-Gomez, E. Tlelo-Cuautle, L. Gerardo de la Fraga and M.A. Duarte-Villasenor, 2012. Selection of MOSFET sizes by fuzzy sets intersection in the feasible solutions space. J. Applied Res. Technol., 10: 472-483.

Sazak, N., I. Erturk, E. Koklukaya and M. Cakiroglu, 2010. An energy efficient MAC protocol for cluster based event driven WSN applications. Proceedings of the International Conference on Telecommunications and Computer Networks, September 23-25, 2010, Split, Dubrovnik, pp: 76-81.

Tang, W., R. Xie, L. Shu and Y.C. Kim, 2011. P-Mac: A cross-layer duty cycle mac protocol towards pipelining for wireless sensor networks. Proceedings of the IEEE International Conference on Communications, June 5-9, 2011, Kyoto, pp: 1-5.

Tlelo-Cuautle, E., I. Guerra-Gomez, M.A. Duarte-Villasenor, L.G. de la Fraga and G. Flores-Becerra *et al*., 2010. Applications of evolutionary algorithms in the design automation of analog integrated circuits. J. Applied Sci., 10: 1859-1872.

Tulone, D. and S. Madden, 2006. PAQ: Time series forecasting for approximate query answering in sensor networks. Proceedings of the 3rd European Conference on Wireless Sensor Networks, February 13-15, 2006, Zurich, Switzerland, pp: 21-37.

Van Dam, T. and K. Langendoen, 2003. An adaptive energy-efficient MAC protocol for wireless sensor networks. Proceeding of the 1st International Conference on Embedded Networked Sensor Systems, November 5-7, 2003, Los Angeles, California, USA., pp: 171-180.

Vickers, G.T. and C. Cannings, 1987. On the definition of an evolutionarily stable strategy. J. Theoretical Biol., 129: 349-353.

Wang, L. and K. Liu, 2007. An adaptive energy-efficient and low-latency mac protocol for wireless sensor networks. Proceedings of the International Conference on Wireless Communications, Networking and Mobile Computing, WiCom 2007, September 21-25, 2007, Shanghai, pp: 2440-2443.

Willett, R., A. Martin and R. Nowak, 2004. Backcasting: Adaptive sampling for sensor networks. Proceedings of the 3rd International Symposium on Information Processing in Sensor Networks, April 26-27, 2004, Rice University, Houston, TX., USA., pp: 124-133.

Ye, W., J. Heidemann and D. Estrin, 2002. An energy-efficient MAC protocol for wireless sensor networks. Proceedings of the 21st Annual Joint Conference of the Computer and Communications Societies, June 23-27, 2002, IEEE Press, New York, pp: 1567-1576.

Ye, W., J. Heidemann and D. Estrin, 2004. Medium access control with coordinated adaptive sleeping for wireless sensor networks. Trans. Networking, 12: 493-506.

Zhou, H., F. Wu and K. Hou, 2008. An event-driven multi-threading real-time operating system dedicated to wireless sensor networks. Proceedings of the International Conference on Embedded Software and Systems, July 29-31, 2008, Sichuan, pp: 3-12.