An Energy-Efficient Transmission Strategy For Wireless Sensor Networks

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Abstract — *In this work we propose an energy-efficient transmission strategy for wireless sensor networks that operate in a strict energy-constrained environment. Our transmission algorithm consists of two components: a binary-decision based transmission and a channel-aware backoff adjustment. In the binary-decision based transmission, decision on whether to transmit or not is absolutely dependent on the current channel conditions. Specifically, transmission is initiated only when the channel quality exceeds a specified threshold, so that unsuccessful transmissions causing a waste of energy are avoided whenever possible. Using the Markov decision process (MDP) formulation we obtain the optimum threshold for successful transmission. A channel-aware backoff adjustment, the second component of our proposal, is introduced to favor nodes with better channel conditions. By intelligently combining these two ingredients our transmission algorithm attempts to maximize energy efficiency. Extensive simulations are performed to verify the performance of our proposal over fading wireless channels. Numerical results show that our transmission algorithm outperforms the existing approaches in terms of energy efficiency, thereby further prolonging the network lifetime*[1].

Index Terms —Wireless Ad-hoc networks, energy efficiency, Markov decision process (MDP), opportunistic transmission.

I. INTRODUCTION

In wireless sensor networks (WSNs) a number of sensor nodes are deployed for data gathering with a small battery that is difficult to replace [1]. Since the WSN may function until a significant fraction of sensor nodes are operational, energy efficiency is a key technical issue in the design of WSN [2]–[4]. Especially, careful management of energy resources is required to maximize the lifetime of the WSN [5].

The nodes operate over the time-varying wireless channel whose quality significantly fluctuates over time due to fading and interference. Such time-varying nature of wireless channel imposes many constraints in designing an energy-efficient transmission scheme. For instance, a transmission attempt, when the wireless channel is temporarily bad, is highly likely to be failed and may lead to a waste of energy. To avoid this, the sender may wait until the channel becomes better. However, deferring the transmissions until the channel becomes better may decrease throughput, or equivalently cause a longer latency. This is a trade-off problem between energy efficiency and throughput. Thus an efficient transmission scheme for the WSNs must be able to adapt to variation of the wireless channel while maintaining a good balance between these two conflicting measures.

Many different techniques have been proposed to increase energy efficiency in the WSNs. In [6] a link adaptation technique was proposed for WSNs. In this paper, the authors proposed an adaptive adjustment of frame size in transmission and the extended Kalman filter was used to predict the optimal frame size. In [7], a transmission scheme adopting multicast Ready-to-Send (RTS) and priority-based Clear-to-Send (CTS) was proposed to prioritize the terminal with a good channel in terms of channel access. In [8], the authors obtained an optimal solution of the problem of buffer and channel adaptive transmission for maximizing system throughput. In [9], transmission rate is dynamically adjusted based on the received signal strength. The Receiver Based Auto Rate (RBAR) protocol in [10] allows the receiver to choose the data rate based on the signal-to-noise ratio (SNR) of the RTS packet.

In this work we propose an energy-efficient scheme for the WSNs under wireless fading channel. Our scheme basically takes an opportunistic transmission approach in which transmissions are attempted only under good channel conditions whenever possible. This idea is realized into two parts of Medium Access Control (MAC) protocol: a binary-decision based transmission (BDT) and a channel-aware backoff adjustment (CBA). In the BDT scheme, whether to initiate transmission or not is determined according to the current channel conditions. By exchanging the control messages like RTS and CTS in the 802.11 standard for channel measurement and its feedback, respectively, the receiver can measure the channel quality and the sender can retrieve such information piggybacked in the return message. To continuously monitor the channel condition, data message and its acknowledgement message are also used to measure and piggyback the channel information. In addition, CBA algorithm is introduced to favor the sensor nodes with better channel conditions. For those sensor nodes which see a better channel recently, a smaller contention window (CW) is

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assigned to access the channel faster, whereas a relatively larger CW is given for the opposite cases.

In the BDT scheme, the MDP formulation [11] is used to obtain the optimum threshold for successful transmission. Moreover, an alternative transmission scheme called fragmented transmission (FT) is investigated to compare with the BDT scheme. In the FT scheme, the sensor node can take another action of fragmented transmission in which an entire frame is transmitted in a series of fragmented frames to avoid transmission failure. Extensive simulations are performed with ns-2 to verify the performance of our proposal over wireless fading channels. Our transmission algorithms are applied to IEEE 802.11 Distributed Coordination Function (DCF) standard with some necessary modifications. The simulation results show that the use of binary-decision based transmission with channel-aware backoff improves energy efficiency by up to 70% with respect to the plain IEEE 802.11 while achieving a comparable throughput.

The remainder of the paper is organized as follows. Section II describes our system model. The proposed transmission algorithm is given in Section III. Section IV presents the MDP formulations for transmission schemes. Section V describes numerical results and simulations and is followed by discussion of related work in Section VI. Finally, we conclude the paper in Section VII.

II. System Model

In this section we give a description on our system model that is concerned with MAC protocol and wireless channel model.

A. MAC Protocol

Our transmission schemes are implemented on IEEE 802.11 DCF standard with some necessary modifications. The modifications are associated with channel measurement and a mechanism for its feedback. As shown in Fig. 1, RTS/CTS and DATA/ACK messages are all used in pair for continuous channel monitoring and feedback of the measurement results.

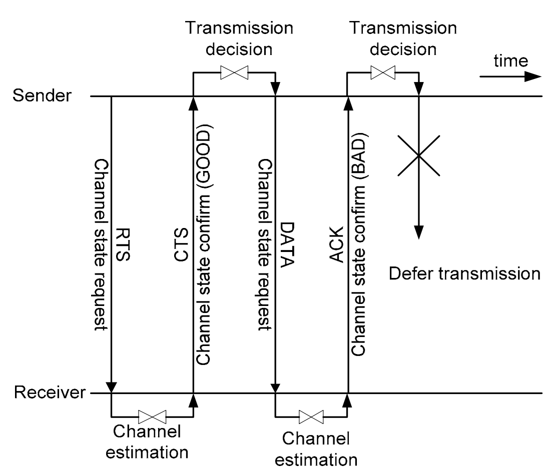

Fig. 1. Channel measurement and feedback via exchanges of control messages

Although 802.11 MAC protocols may not be suitable for WSNs, we employ it in this work to demonstrate effectiveness of our transmission schemes. Since our schemes require only exchange of short control messages or piggybacking in normal data messages for delivery of channel-related information, they are readily applicable to different MAC protocols other than IEEE 802.11 DCF protocol.

B. Channel Model

A finite-state Markov channel (FSMC) model is used to capture the time-varying behavior of wireless fading channel [12]. In Rayleigh fading channels, the received instantaneous SNR (y) is exponentially distributed with probability density function:

$$f_y(y) = \frac{1}{\rho} e^{-\frac{y}{\rho}}$$

where $\rho = E[y]$. Let y_i denote the threshold of the received SNR where $0 = y_0 < y_1 < y_2 < \ldots < y_K = \infty$. The channel is said to be in state g_k, $0 \leq k < K$, if the received SNR is in the interval $[y_k, y_{k+1})$. We assume that the transitions in the FSMC model occur at the boundary of time slot in which one fixed-size frame is transmitted and transitions occurs only between adjacent states, as shown in Fig. 2. Furthermore, the channel gain is constant during one time slot of transmission. The parameters of the Markovian channel can be obtained by using the techniques in [12].

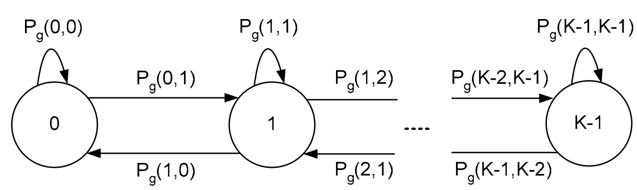

Fig. 2. Finite-state Markov channel model

We denote $N(y)$ as the level crossing rate given by

$$N(y) = \sqrt{\frac{2\pi y}{\rho}} f_m e^{-y/\rho}$$

where f_m is the maximum Doppler frequency. The state transition probabilities are given by

$$P_g(k, k+1) = N(y_{k+1}) \frac{T_f}{\pi_k}, \quad 0 \leq k \leq K-2$$

$$P_g(k, k-1) = N(y_k) \frac{T_f}{\pi_k}, \quad 1 \leq k \leq K-1$$

where T_f is the frame transmission time and π_k is the steady state probabilities given by

$$\pi_k = \int_{y_k}^{y_{k+1}} f_y(y) dy$$

For BPSK case, the probability of symbol error $P_b(g_k)$ for state g_k is given by

$$P_b(g_k) = \frac{\delta_k - \delta_{k-1}}{\pi_k} \tag{1}$$

where

$$\delta_k = e^{-\frac{y_k}{\rho}}\left(1 - F\left(\sqrt{2y_k}\right)\right) + \sqrt{\frac{\rho}{\rho+1}}F\left(\sqrt{\frac{2y_k(\rho+1)}{\rho}}\right)$$

and *F(x)* denotes the cumulative distribution function (CDF) of a standard normal random variable

$$F(\alpha) = \int_{-\infty}^{\alpha} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx$$

Throughout this paper the error statistics follow the BPSK case as formulated above.

III. Transmission Algorithm

In this section we describe our transmission algorithm designed to maximize energy efficiency. Our algorithm consists of two components: BDT and CBA.

A. Binary-Decision Based Transmission

In this scheme the sensor node takes either of two actions: *Transmit* and *Defer*, corresponding to transmitting the data and deferring the transmission, respectively. As shown in Fig. 1, current wireless channel is measured at the receiver via RTS or Data frame, and is classified into one of two states including *Good* and *Bad* based on the received SNR. This information is notified back to the sender by embedding it in the return frame, i.e., CTS or ACK frame. The SNR threshold used to classify the channel states is determined using the Markov decision process (MDP) as explained in detail in the following section.

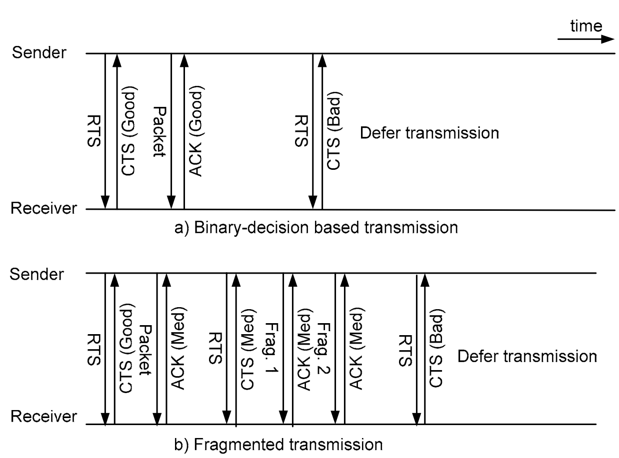

Fig. 3. Binary-decision based transmission and fragmented transmission

An alternative technique for improving energy efficiency is fragmenting a full-sized frame into multiple subframes and transmitting one-by-one so as to reduce the frame error rate [6]. This scheme is named Fragmented Transmission (FT). We also analyzed this scheme to compare with the BDT. The behavior of FT is similar to that of BDT, except that the channel is classified into three states including *Good*, *Medium* and *Bad*. Upon seeing the channel of *Medium* state the sender transmits fragmented frames. In order to classify the channel states into those three states, the FT scheme has two thresholds: *Fragment threshold* and *Transmit threshold*. The channel states with SNR value greater than *Fragment threshold* is classified into *Good* state in which a full-sized frame is transmitted, whereas the channel states with SNR value less than *Transmit threshold* is classified into *Bad* state in which transmission is deferred. The in-between channel states are classified into *Medium* state. Regarding granularity of fragmentation, we assume a full-sized frame can be broken into n equal-sized fragmented frames. Figure 3 depicts the differences between BDT and FT schemes.

B. Channel-Aware Backoff Adjustment

In IEEE 802.11 DCF standard, the Binary Exponential Backoff (BEB) algorithm is used for contention resolution. In this work we propose a new algorithm called a CBA. This scheme is based on the BEB algorithm, but some modifications are made to enhance energy efficiency by exploiting the time varying nature of wireless channel.

Under slow fading channel, the wireless channel varies slowly over time. If the channel is good at present, then it is more likely that the channel remains good in the near future. This characteristic is exploited in our algorithm by prioritizing the sensor nodes, currently or recently seeing a good channel, in terms of channel access. Such differentiation is realized by assigning different sizes of contention window (CW) to the sensor nodes based on the channel quality.

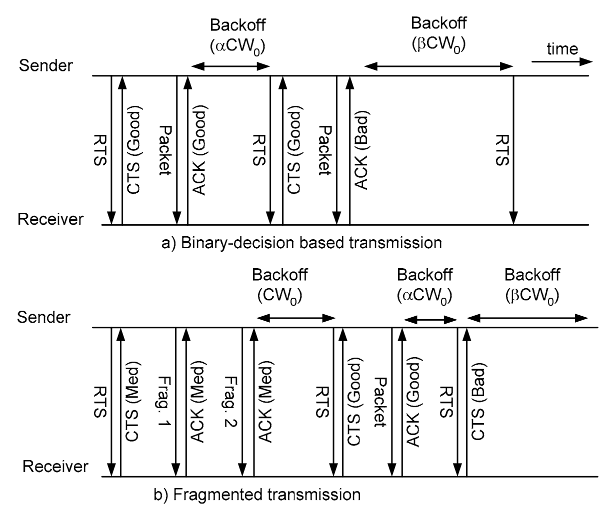

Fig. 4. Backoff-based priority scheme

The details of the CBA algorithm are described as follows. Every sensor node maintains a table called Link State Table that lists up the channel states of each link to its neighbors and their validity information. For each link, a pair of (Channel State, Validity) information is maintained. Such information in this table is updated when the sensor node gets a new channel information state via an exchange of messages, or when a specified validity period elapses from the last update. The validity period is set to channel coherence time that can be estimated from on-line measurements.

The initial CW is set according to the channel state:

$$CW = \begin{cases} \alpha(t).CW_0, & \text{upon Good channel} \\ CW_0, & \text{upon Medium channel or} \\ & \text{expired channel information} \\ \beta(t).CW_0, & \text{upon Bad channel} \end{cases}$$

where $\alpha(t)$ and $\beta(t)$ are multiplicative constants for prioritizing the nodes seeing good and bad channel, respectively, and t is a timer value, initially set to the validity period T, decremented over time. In this paper, the validity period T is chosen as same as the average fade duration and given by [13], [14].

If the timer expires, $\alpha(t)$ and $\beta(t)$ set to 1 and the validity field in *Link State Table* is set to invalid. Note that $\alpha(t)$ and $\beta(t)$ remain effective even after consecutive collisions as long as the timer does not expire. Throughout this paper we assume that $\alpha(t) = 1/2$ and $\beta(t) = 3/2$ unless stated otherwise. An exact analysis of these settings will be investigated elsewhere. Operation of our transmission algorithms including the BDT, FT, and CBA is shown in Fig. 4.

IV. MARKOV DECISION PROCESS (MDP)

In this section the problem of finding the optimum thresholds for successful transmission is formulated using the MDP. For both BDT and FT, the optimum operation policy in terms of energy efficiency is obtained. For the sake of tractable analysis, it is assumed that time is divided into time slots of equals length of T_f seconds. In addition, the time slot is assumed to be sufficiently short and the traffic load is light such that a frame arrives at each time slot following a Bernoulli distribution with parameter λ. To consider the applications that require up-to-date sensing data under light traffic load, we assume that the buffer can hold at most one frame. Thus any new coming frame preempts the existing one and the existing frame is dropped. It is also assumed that the outcome of transmission is immediately available at the end of transmission.

A. Binary-Decision Based Transmission

1) System States: We denote the set of possible system states by **S** in which **S** is a finite set. The system state s_i at time slot i is given by

$$s_i = \langle g_i, t_i \rangle$$

where g_i is the channel state at time slot i, $0 \le g_i < K$, and t_i is the state of sensor node at time slot i. The possible states of the sensor node include *Idle* and *Active*. The sensor node is said to be in *Active* state when a frame is in the buffer waiting for transmission and in *Idle* state when no frame is present.

2) Control Actions: Depending on system state s_i, sensor node determines to transmit or to defer transmission. Let $A(s_i)$ denote the set of all possible control actions in state s_i and a_i be the control action executed at time slot i. Each action in $A(s_i)$ corresponds to the following values:

$$a_i = \begin{cases} 0, & \text{Defer} \\ 1, & \text{Transmit} \end{cases}$$

3) Cost of Actions: In *Idle* state, the sensor node takes no actions and thus the cost of actions equals zero. In *Active* state, the immediate cost incurred at time slot i is defined as

$$C_i(s_i, a_i) = E_c + L_e(g_i, a_i)E_t + \delta L_d(g_i, a_i) \quad (2)$$

where E_c and E_t are energy consumption per bit for sending control packet and data packet, respectively; δ is a weighting factor that indicates a relative importance of frame loss over energy consumption; $L_e(g_i, a_i)$ is the expected frame error rate; and $L_d(g_i, a_i)$ is the expected number of frame losses due to buffer overflow. $L_e(g_i, a_i)$ is given by

$$L_e(g_i, a_i) = a_i P_f(g_i) \quad (3)$$

where $P_f(g_i)$ is the frame error rate when the channel state is g_i. Assuming independent bit errors, the frame error rate $P_f(g_i)$ for frame size L and the channel state g_i is given by

$$P_f(g_i) = 1 - \left(1 - P_b(g_i)\right)^L \quad (4)$$

where $P_b(g_i)$ is obtained from (1). $L_d(g_i, a_i)$ is given by

$$L_d(g_i, a_i) = \lambda\left((1 - a_i) + a_i P_f(g_i)\right) \quad (5)$$

4) System Dynamics: Given the system state $s_i = \langle g_i, t_i \rangle$ and a control action a_i, the probability of the system being state $s_{i+1} = \langle g_{i+1}, t_{i+1} \rangle$ in next time slot is:

$$\begin{aligned} \Pr\left[s_{i+1} = \langle g_{i+1}, t_{i+1} \rangle \mid s_i = \langle g_i, t_i \rangle, a_i = a \right] \\ = P_g(g_i, g_{i+1}) P_t(t_i, t_{i+1}, a) \end{aligned} \quad (6)$$

where $P_g(g_i, g_{i+1})$ is the transition probability from channel state g_i to g_{i+1} and $P_t(t_i, t_{i+1}, a)$ is the transition probability of sensor node state from t_i to t_{i+1} under the given control action a. Figure 5 depicts the state diagram of the behavior of sensor node in which the transition probability $P_t(t_i, t_{i+1}, a)$ and the corresponding cost of action is provided.

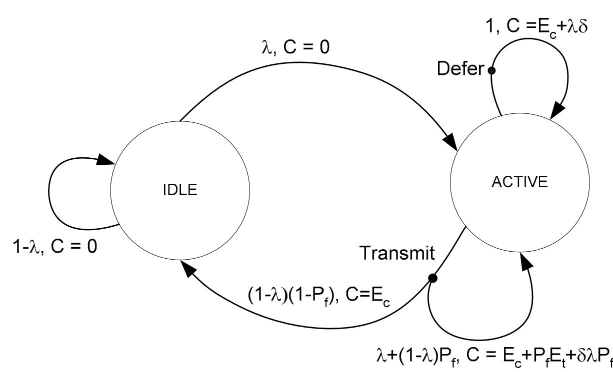

Fig. 5. State diagram of the BDT scheme

5) Average Cost: Let $\pi = \{\mu_0, \mu_1, \mu_2, \ldots\}$ be a policy which maps system states into control actions. Our objective is to minimize over all policies π with $\mu_t : S \to A, \mu_i(s) \in A(i)$ for i and s, the average cost per stage

$$J_\pi(s) = \lim_{T \to \infty} \frac{1}{T} \left\{ \sum_{i=0}^{T-1} C\left(s_i, \mu(s_i)\right) \mid s_0 = s \right\} \quad (7)$$

We need to choose an optimal policy π to minimize this cost:

$$\pi^* = \arg\min_\pi J_\pi(s) \quad (8)$$

Our model is a unichain MDP model. Therefore, a stationary policy and an optimal average cost for this problem can be obtained by using the relative value iteration algorithm in the dynamic programming techniques [8], [15].

B. Fragmented Transmission

1) System States: Let $\boldsymbol{S}$ denote the set of possible system states. The system state s_i at time slot i is given by

$$s_i = \langle g_i, t_i \rangle$$

where g_i is the channel state at time slot i, $0 \le g_i < K$, and t_i is the state of sensor node at time slot i. The possible states of the sensor node include *Idle*, *Active*, and n-1 *Fragment* states. Let I, F_n, and F_k (k = 1, 2, …, n-1) denote *Idle*, *Active*, and *Fragment* states with k fragments remaining, respectively. Similar to the BDT scheme, the sensor node is said to be in *Active* state when a frame is in the buffer waiting for transmission and in *Idle* state when no frame is present. The sensor node is said to be in k^{th} *Fragment* state denoted by F_k when k fragmented frames out of n remain in the buffer.

2) Control Actions: The sensor node can choose one of three possible control actions at each state, namely: *Transmit*, *Defer*, and *Fragment*. Let *A(s)* denote the set of all possible control actions in state s and a_i denote the control action executed at time slot i and its value is assigned by the following:

$$a_i = \begin{cases} 0, & \text{Defer} \\ 1, & \text{Transmit} \\ 2, & \text{Fragment} \end{cases}$$

3) Cost of Actions: Given the system state s_i and a control action a_i, the immediate cost incurred in time slot i is obtained in the same way as the BDT scheme. In Idle state, the sensor nodes take no actions and thus the cost of actions equals zero. For other states, the cost of actions can be obtained as follows.

For the actions of *Defer* ($a_i = 0$) and *Transmit* ($a_i = 1$), the immediate cost $C_i(F_k, g_i, a_i)$ is given by

$$\begin{aligned} C_i(F_k, g_i, a_i) = E_c + a_i\left((1-\lambda)k + n\lambda\right)P_f^{(k)}(g_i)\frac{E_t}{n} \\ + (1-a_i)\lambda\frac{(n-k)}{n}E_t \\ + \lambda\delta\left(1 - a_i\left(1 - P_f^{(k)}(g_i)\right)\right) \end{aligned} \quad (9)$$

where $P_f^{(k)}(g_i)$ is the transmission error probability of the frame that is formed by k fragmented frames of equal size. This probability can be easily obtained from (4) by replacing L by kL/n.

For the action *Fragment* ($a_i = 2$), the immediate cost $C_i(F_k,g_i,a_i)$ is given by

$$\begin{aligned} C_i(F_k, g_i, a_i) = E_c + \Bigg((1-\lambda)\sum_{m=1}^{k} L_e(g_i, m) \\ + \lambda\sum_{m=1}^{k}(n-k+m)L_e(g_i, m)\Bigg)\frac{E_t}{n} \\ + \delta\lambda\sum_{m=1}^{k} L_e(g_i, m) + \sigma \end{aligned} \quad (10)$$

where σ is the fragmentation cost (incurred from the processing overhead, etc.) when the sender takes the fragment action instead of the transmit action, and $L_e(g_i, m)$ is the probability that the consecutive fragmented transmissions stop during the Fragment action because of the transmission failure of m^{th} fragmented frame and is given by

$$L_e(g_i, m) = \left(1 - P_f^{(1)}(g_i)\right)^{m-1} P_f^{(1)}(g_i) \quad (11)$$

Recall that the fragmented frames are transmitted in sequence during the Fragment action until the first transmission failure occurs.

4) System Dynamics: In this FT model, three factors control the dynamics of system: channel variation, arrival of new frame, and control actions. Similar to the BDT scheme, the system dynamics can be expressed by (6). When the sensor node is in *idle* state, the transition probability does not depend on control actions. In this case that is given by

$$P_t(I, F_n, .) = \lambda$$
$$P_t(I, I, .) = 1 - \lambda$$

When the sensor node is in active state or fragment state, the transition probability depends on the control action, frame error rate, and arrival of new frame. It can be obtained as follows:

$$\begin{aligned} &P_t(F_k, F_k, 0) = (1-\lambda) + 1(k=n)\lambda \\ &P_t(F_k, I, 1) = (1-\lambda)\left(1 - P_f^{(k)}(g)\right) \\ &P_t(F_k, F_k, 1) = (1-\lambda)P_f^{(k)}(g) + 1(k=n)\lambda \\ &P_t(F_k, F_i, 2) = (1-\lambda)\left(P_f^{(1)}(g)\right)\left(1 - P_f^{(1)}(g)\right)^{k-i} \\ &\qquad + 1(k=n, i=n)\lambda, \quad 1 \le i \le k \le n \\ &P_t(F_k, I, 2) = (1-\lambda)\left(1 - P_f^{(1)}(g)\right)^{k} \\ &P_t(F_k, F_n, a) = \lambda, \quad k < n, \forall a \end{aligned}$$

where *1(e)* is the indicator function for the event e.

5) Average Cost: Based on the system dynamics and immediate cost which have been characterized above, we can formulate the MDP as in the BDT scheme. Similarly, the dynamic programming techniques can be used to obtain the optimal policy.

V. NUMERICAL RESULTS AND SIMULATIONS

In this section we analyze the performance of our transmission schemes, namely, BDT, FT, and CBA, under various operating conditions. We also perform extensive simulations with ns-2 simulator to verify the performance of our schemes in terms of energy efficiency and throughput. We consider 30 nodes randomly dispersed over a network field (100m × 100m) and 1 sink node located at the center. Each sensor nodes generate a frame of 128 bytes, destined to the sink node directly, every 1 second. Wireless fading channel is modeled by 20-state Markov chain model. Table I summarizes the values of the various parameters used in our experiments. Note that T_f in our simulation is configured to match the period in which sending and receiving nodes complete the exchange of RTS, CTS, DATA, and ACK frames using RTS/CTS mechanism. Besides the additive parts of 802.11 such as IP header and MAC header are tripped off in our simulations.

TABLE I
PARAMETER VALUES USED IN THE SIMULATIONS AND NUMERICAL RESULTS

Parameters	Value (default)
Number of sensor nodes	30
Frame transmission time (T_f)	1ms
Transmission range of sensor node	75m
Traffic model of sensor nodes	CBR
Packet interval	1s
Packet size (including headers) (L)	128 (bytes)
Control packet size	10 (bytes)
Average SNR	10 dB
Frame arrival probability (λ) in MDP	0.02
Weighting factor in cost function (δ)	0.5
Fragmentation cost (σ)	0.01
Number of fragments per frame (n)	2
Simulation time	1000 s

A. *Optimum Thresholds for BDT and FT*

We first analyze how the optimum threshold for successful transmission varies under different channel conditions. Figure 6 shows the optimum transmit and fragment thresholds of BDT and FT, versus average SNR. Recall that the FT scheme has two thresholds: Fragment threshold for transmitting original frame or transmitting fragmented frames, and Transmit threshold for transmitting fragmented frames or deferring transmission. As shown in the figure, all the thresholds tend to increase as the average SNR becomes higher. This result seems somewhat obvious. One interesting observation here is that all the thresholds are eventually merged into one for average SNRs higher 18 dB. This is because fragmentation has little gains in an extremely good channel condition.

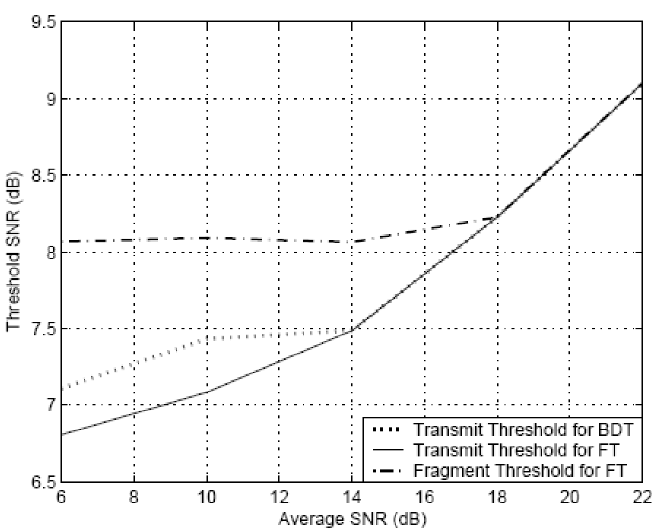

Fig. 6. The optimum thresholds of BDT and FT versus average SNR (ρ).

Figure 7 shows the optimum transmit and fragment thresholds in dB of BDT and FT, for varying Doppler frequency. As shown in the figure the optimum values increase as Doppler frequency become larger. This result indicates that deferring the transmission is more favorable in a fast varying channel. In a slow fading channel, deferring the transmission is not beneficial since the channel will not become better in the near future when the node currently sees bad channel. Thus the threshold should be set to be lower. However, a higher threshold is preferred under fast fading channel to prioritize the defer decision.

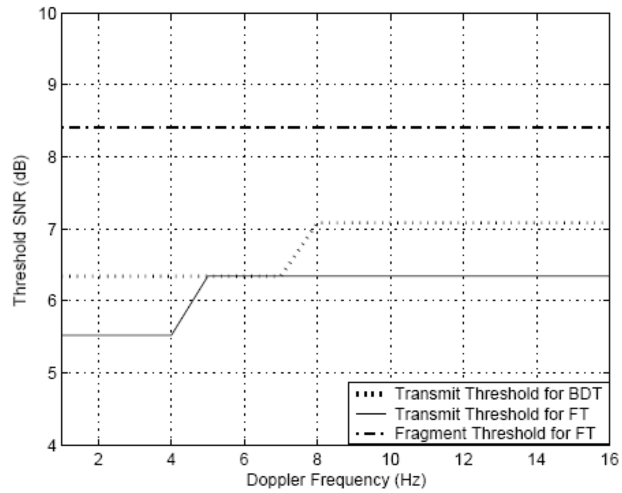

Fig. 7. The optimum thresholds of BDT and FT versus Doppler frequency (f_m).

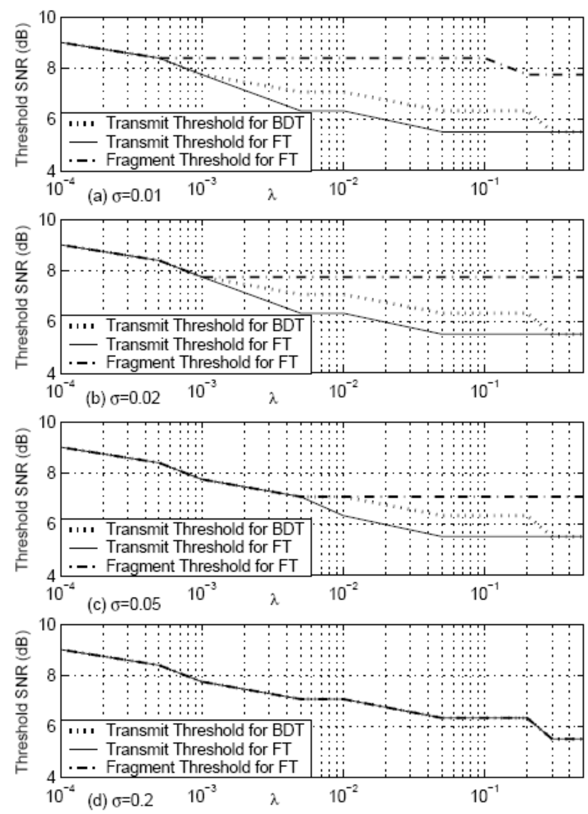

Fig. 8. The optimum thresholds of BDT and FT versus frame arrival probability (λ).

Figure 8 shows the optimum thresholds of BDT and FT schemes for varying frame arrival probability ($0.0001 \leq \lambda \leq 0.1$) and fragmentation cost ($0.01 \leq \sigma \leq 0.2$). The set of figures in

Fig. 8 well illustrates the characteristics of the optimum thresholds under varying network conditions. For a given fragmentation cost, there exists a range of traffic load in which the fragment action is not taken (e.g., $\lambda \leq 0.0005$ for Fig. 8(a)). These ranges extend further as the fragmentation cost increases. For a given fragmentation cost, there is a light-traffic region in which the fragmentation cost is more significant than the cost due to buffer overflow, thus the fragment action is not necessary. However, as the traffic becomes heavier, the cost due to buffer overflow becomes dominant and the transmit threshold accordingly becomes lower. This leads to more transmission failures, thereby requiring the fragment action to avoid the transmission failure. As an extreme case, Fig. 8(d) shows that both thresholds of the FT scheme converges to the transmit threshold of the BDT scheme. In addition, we observe that the fragment threshold is insensitive to traffic load and is solely dependent on the fragmentation cost.

B. Comparison of BDT and FT in Energy Efficiency

Figure 9 shows the ratio of costs of two schemes, i.e., cost of FT/cost of BDT, under various operating conditions. Recall that the cost of each transmission scheme is defined in (2) and (9). As shown in this figure, the cost of FT is less than that of BDT by up to 14% except the cases of relatively higher fragmentation cost and lighter traffic load. From Figure 9(a) we observe the fragmented transmission has less cost to a certain traffic load ($\lambda \leq 0.02$ for $\sigma = 0.01$), but it loses the gain beyond it.

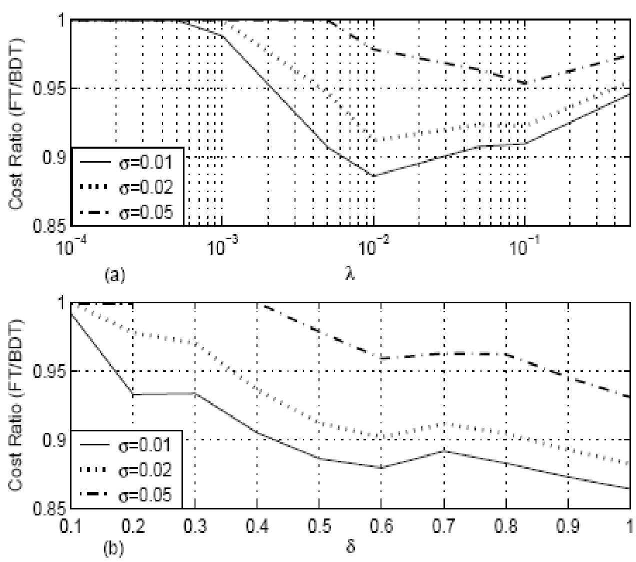

Fig. 9. The ratio of the cost of FT over BDT versus frame arrival probability (λ) and weighting factor (δ).

It is also observed that the cost ratio of FT over BDT is monotonically decreasing as a function of δ. This implies that the fragment action is favorable as the cost due to buffer overflow approaches closer to the power consumption incurred by a single frame transmission. Figure 10 shows the cost ratio of two schemes for varying Doppler frequency. As shown in this figure, FT gains an advantage over BDT; however, it is manifested that this advantage diminishes as the channel varies mode rapidly.

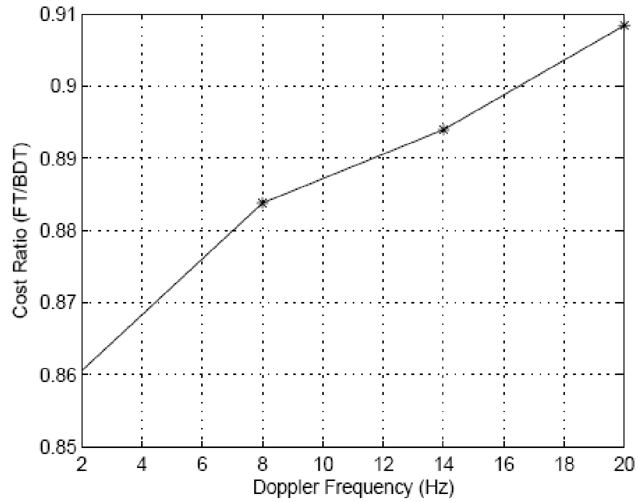

Fig. 10 The ratio of the cost of FT over BDT for varying Doppler frequency

C. Energy Efficiency of BDT and FT versus 802.11

Figure 11 shows simulation results of energy efficiency for three transmission schemes: BDT with CBA, FT with CBA, and 802.11 over the Doppler frequency range of 2 to 10Hz. Here the energy efficiency is defined as the ratio of the number of successful transmissions over the number of transmission attempts. As shown in the figure, the BDT with CBA, FT with CBA, and 802.11 has the energy efficiency of 0.9, and 0.88, and 0.50, respectively (f_m = 8Hz). A significant improvement, more than 70 %, is achieved with the both BDT with CBA and FT with CBA schemes, compared with the plain 802.11. Such energy conservation mostly comes from the reduction in the number of frame loss due to transmission errors. However, such gains do not come for free. As shown in the next figure, our transmission scheme based on the opportunistic transmission sacrifices throughput by deferring the transmission when the channel state is bad.

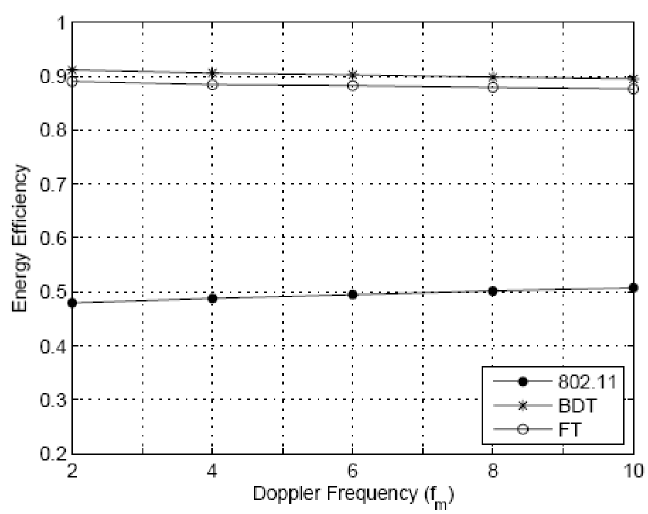

Fig. 11. Energy efficiency of three transmission schemes: BDT with CBA, FT with CBA, and 802.11.

D. Throughput and En-to-End delay of BDT and FT versus 802.11

Figure 12 shows throughput of three alternative transmission schemes: BDT with CBA, FT with CBA, and 802.11. Throughput is observed at the sink node and averaged over the simulation time. As shown in the figure, 802.11, FT with CBA has higher throughput than BDT with CBA, although the gap is not significant. As mentioned earlier, a higher energy efficiency can be achieved at the expense of throughput. Considering the trade-off issue, we can see throughput performance of BDT with CBA and FT with CBA are not significantly deteriorated. Moreover, the attempt to transmit packets in worse channel conditions can gain little in throughput. Even worse, it negatively increases the average end-to-end latency as shown in Figure 13.

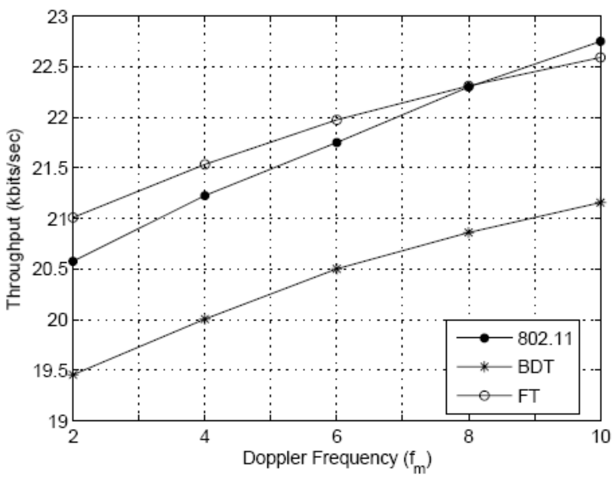

Fig. 12. Throughput of three transmission schemes: BDT with CBA, FT with CBA, and 802.11.

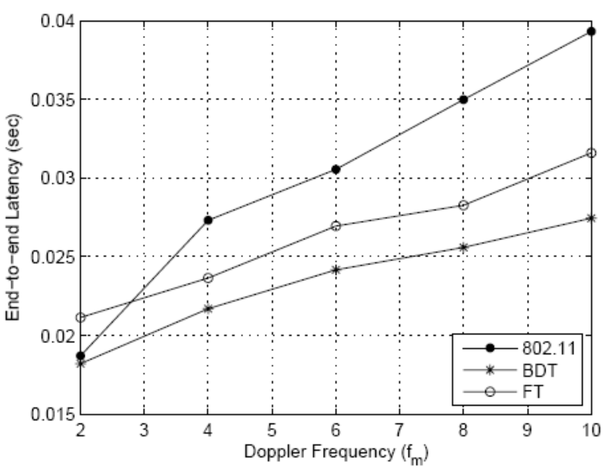

Fig. 13. Delay of three transmission schemes: BDT with CBA, FT with CBA, and 802.11.

VI. RELATED WORK

At the time of this work, several prior works addressed the problem of designing energy-efficient transmission strategies for wireless sensor networks. In fact, a large fraction of the works employs the MDP formulation to solve the problems. In [8], the optimum transmission power and modulation scheme are chosen to obtain the maximum system throughput under the constraint of transmission power. This optimization problem is formulated as an MDP and the dynamic programming technique is used to obtain the solution. In [16], the authors solved the problem of finding the optimum modulation level and transmission power to maximize the long term average throughput per total consumed energy. In this paper, the authors also used the MDP to formulate the optimization problem and a near optimum solution is obtained by using the reinforcement learning algorithm. Another work using the MDP to find the optimum policies for transmission strategy was reported in [17]. In this paper, both the transmission power and the probability that the blocked users attempt a packet transmission in a slot are optimized to maximize system throughput.

Some works [14], [18], [19] attempted to utilize the channel information to achieve energy efficiency in wireless sensor networks. In [14], the channel status and the fade duration of the channel are predicted at the receiver based on the previous received packets. This information is used to control the transmission scheme at the sender. The aim of this approach is to save the transmission power and to better utilize the bandwidth resources in the vicinity of the transmitter. In [19], the authors derived a general formula for network lifetime in terms of two crucial parameters including the channel state and the residual energy of sensors. An MAC protocol based on this formula, referred to as max-min protocol, was proposed to maximize the network lifetime by exploiting these parameters of each sensor. Furthermore, a distributed implementation of the max-min protocol was investigated in [18], which allows each sensor to determine whether to transmit based on its own channel state and the amount of residual energy. In [20], the authors used the dynamic programming technique to develop optimum transmission strategies over a wireless fading channel, given energy, power and deadline constraints. Given that the channel state determines the throughput obtained per unit of energy expended, a dynamic programming formulation is developed to obtain a policy for scheduling transmissions that maximizes the expected data throughput.

Stochastic control algorithms were used to control packet transmission probability over a time varying wireless channel. The Stop-and-Wait Automatic Repeat reQuest (ARQ) transmission control problem for uplink channels is formulated as a Markovian search problem in [21]. In [22], a transmission scheme for wireless data communication over time varying channels with memory has been investigated.

VII. CONCLUSION

We proposed an energy-efficient transmission strategy for WSNs that operates in a strict energy-constrained environment. The proposed algorithm significantly improves energy efficiency without additional complexity. Our transmission algorithm consists of two components: an opportunistic transmission and a channel-aware backoff adjustment. The MDP formulation was used to obtain the optimum threshold of channel quality for the opportunistic transmission. By intelligently combining these ingredients our transmission algorithm outperforms the existing approaches in terms of energy efficiency, thereby prolonging the network lifetime further. For future extension, varying transmission slot instead of fixed time slot assumed in this work can be modeled by semi-Markov decision process.

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