Energy Efficient Transmission Strategies for Body Sensor Networks with Energy Harvesting

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***Abstract*— This paper addresses the problem of developing energy efficient transmission strategies for Body Sensor Networks (BSNs) with energy harvesting capabilities. It is assumed that two transmission modes that allow a tradeoff between the energy consumption and packet error probability are available to the sensors. Decision policies are developed to determine the transmission mode to use at a given instant of time in order to maximize the quality of coverage. The problem is formulated in a Markov Decision Process (MDP) framework and an upper bound on the performance of arbitrary policies is determined. Our results show that the quality of coverage associated with the MDP formulation outperforms the other policies.**

I. Introduction

Many applications and services are expected to significantly benefit from the monitoring and data collection services that will be provided by Body Sensor Networks (BSNs) [13], which consist of a number of networked real time sensors and actuators are placed on or inside the human body. These applications and services include medical applications such as diagnostic techniques [9], health and stress monitoring [7], management of chronic diseases [5], and patient rehabilitation [1], as well as non medical applications and services such as biometrics [3], activity monitoring and learning [12] and sports and fitness tracking [4].

One major hurdle for the wide adoption of the BSN technology is the energy supply [11]. The current battery technology does not provide a high enough energy density to develop BSN nodes with sufficiently long life and acceptable cost and form factor. Moreover, the relatively slow rate of progress in the battery technology (compared to computing and communication technologies) does not promise battery driven BSN nodes in near future [8]. The most promising approach to deal with the energy supply problem for BSNs is energy harvesting or energy scavenging [13]. In this approach the nodes have an energy harvesting device that collects energy from ambient sources such as vibration and motion, light, and heat. However, to improve the performance of energy harvesting BSNs to a level that can be widely adopted, progress needs to be made both in energy harvesting techniques and communication policies and protocols. Harvesting aware communication techniques that take into account and exploit the energy harvesting characteristics are particularly needed to optimize the operation of the BSN.

This paper uses the idea of trading off the energy spent on communications with the corresponding reliability thus achieved for developing adaptive transmission policies that aim to maximize the likelihood of sensors detecting and correctly reporting events of interest. The sensors are assumed to have the ability to choose from a set of available transmission modesfor transmitting their data, with each scheme consuming a different amount of energy. However, each scheme has a packet error probability that is a decreasing function of the energy used on transmission. The policies developed exploit the sensor's knowledge of its current energy level and the state of the processes governing the generation of data and battery recharge to select the appropriate transmission mode for a given state of the system. The transmission scheduling problem is then formulated as a Markov Decision Process. An upper bound on the performance of any arbitrary policy is obtained.

The rest of the paper is organized as follows. Section II describes the system model. Upper bounds on the performance of arbitrary communication strategies are developed in Section III. A Markov Decision Process formulation of the problem is presented in Section IV, simulation results are presented in Section V and Section VI concludes the paper.

II. System Model

We consider a discrete time model where time is slotted in intervals of unit length. Each slot is long enough to transmit one data packet and at most one data packet is generated in a slot.

Each sensor is considered to have a rechargeable battery and an associated energy harvesting device. The harvesting device uses one of many possible underlying physical phenomena to generate energy and the rate at which it does so is dependent on its ambient conditions. For analytical tractability, we assume that the energy generation process of the sensor is modeled by a correlated, two-state process. In its on state (i.e. when ambient conditions are conducive to energy harvesting), the sensor generates energy at a constant rate of c units in a time slot. In the off state, no energy is generated. We consider a correlated model for describing the transition between the two states. If the sensor harvested energy in the current slot, it harvests energy in the next slot with probability q_{on}, with $0.5 < q_{on} < 1$, and no energy is harvested with probability $1 - q_{on}$. On the other hand, if no energy was harvested in the current slot, no energy is harvested in the next slot with probability q_{off}, $0.5 < q_{off} < 1$ and energy is harvested with probability $1 - q_{off}$. To keep the analysis tractable, our model assumes that the capacity of the battery in each sensor is infinite. This assumption is relaxed in Section IV where a MDP formulation is used to develop transmission strategies in realistic scenarios.

The process governing the generation of events or equivalently data packets that the sensors report to the sink are also governed by a correlated, two-state process. If an event if generated in the current slot, another event is generated in the next slot with probability p_{on}, $0.5 < p_{on} < 1$ and no event is generated is $1 - p_{on}$. Similarly, if no event is generated in the current slot, no event is generated in the next slot with probability p_{off}, $0.5 < p_{off} < 1$ while an event is generated with probability $1 - p_{off}$. To obtain the average duration of a period of continuous events, consider a time slot t such that no event occurred in slot $t-1$ but an event occurred in slot t. Let N be the random variable denoting the number of time slots, including t, after which no events are generated again. Then

$$P[N = i] = (p_{on})^{i-1}(1 - p_{on}) \quad (1)$$

$$E[N] = \sum_{i=1}^{\infty} i(p_{on})^{i-1}(1 - p_{on}) = \frac{1}{1 - p_{on}} \quad (2)$$

and the steady-state probability of event occurrence is given by

$$\pi_{on} = \frac{1 - p_{off}}{2 - p_{on} - p_{off}} \quad (3)$$

Similarly, the average length of a period without events is $\frac{1}{1-p_{off}}$ and $\pi_{off} = 1 - \pi_{on}$. Along the same lines, the average length of a period with energy harvesting and the steady-state probability of such events are $\frac{1}{1-q_{on}}$ and $\mu_{on} = \frac{1-q_{off}}{2-q_{on}-q_{off}}$, respectively. Finally, the expected length of periods without recharging and its steady-state probability are $\frac{1}{1-q_{off}}$ and $\mu_{off} = 1 - \mu_{on}$, respectively.

In each slot, a sensor consumes δ_0 units of energy to run its circuits. If a sensor decides to transmit data in a slot, additional energy is expended. Each sensor is assumed to have to capability to communicate at two transmission modes: "transmission mode 1" consumes δ_1 units of energy on the modulation, coding and transmission and achieves an expected packet error rate of $1 - \rho_1$ while "transmission mode 2" consumes δ_2 units of energy with an expected packet error rate of $1-\rho_2$. We have $\delta_1 > \delta_2$ and $\rho_1 > \rho_2$ allowing a tradeoff between the energy consumed and reliability. For many medical applications it is more important to deliver the most recent data without delay rather than queue them behind retransmission attempts. Also, delayed data in these scenarios loses much of its value in the presence of more recent data. Since data is generated in continuous bursts in our model, we thus assume that no retransmissions are attempted for packets with error. Also, a sensor is considered available for operation if its energy is greater that $\delta_0 + \delta_2$. If a sensor's energy level falls below this threshold, it moves to the *dead* state where it is incapable of detecting and reporting events and stays there until it harvests enough energy. A node does not spend any energy in the dead state.

The communication strategy of a sensor is governed by a policy Π that decides on the transmission mode to be used for reporting an event. The action taken by the sensor in time slot t is denoted by a_t with $a_t \in \{0, 1, 2\}$ denoting no transmission, and transmissions at mode 1 and 2, respectively. The decision may be based on the current battery level of the sensor and the states of the recharge as well as the event generation process, with the basic objective of maximizing the *quality of coverage*, defined as follows. Let $\mathcal{E}_o(T)$ denote the number of events that occurred in the sensing region of the sensor over a period of T slots in the interval $[0, T]$. Let $\mathcal{E}_d(T)$ denote the total number of events that are detected and correctly reported by the sensor over the same period under policy Π. The time average of the fraction of events detected and correctly reported represents the quality of coverage and is given by

$$U(\Pi) = \lim_{T\to\infty} \frac{\mathcal{E}_d(T)}{\mathcal{E}_o(T)} \tag{4}$$

III. An Upper Bound on the Performance

In this section we present an upper bound on the performance of any possible operating policy. Our fomulation is based on [6]. Let T_1 be the number of slots in which a sensor was alive (i.e. not in the dead state) over the period $[0, T]$ consisting of T slots under the optimal policy Π_{OPT}. Let $P_S(t)$ denote the success probability of the sensor at time slot t under policy Π_{OPT}. $P_S(t)$ signifies the probability that an event occurs in time slot t and is successfully reported given that the sensor was not in the dead state in slot t. We use the definition $P_S(t) = 0$ if the sensor is in the dead state in time t. The steady-state success probability is denoted by $\bar{P}_S$ and is given by

$$\bar{P}_S = \lim_{T\to\infty} \sum_{t=1}^{T} \frac{P_S(t)}{T_1} \tag{5}$$

Since $\bar{P}_S$ is the steady-state probability of detecting and successfully reporting an event we also have

$$\bar{P}_S = \lim_{T\to\infty} \frac{\mathcal{E}_d(T)}{T} \tag{6}$$

We denote by γ_1 the fraction of slots with transmission attempts in which the policy uses transmission mode 1 and by γ_2 the fraction of slots with transmission attempts using transmission mode 2. Let ρ_t denote the probability that a transmission attempt in slot t is successful and E_t (E_t^c) denote the event that a data packet to be reported is (not) generated in slot t. The probability of successfully detecting and reporting an event at time $t + 1$ can be written as

$$\begin{aligned} P_S(t) &= P[E_t, \rho_t \mid a_t] \;=\; \frac{P[E_t, \rho_t, a_t]}{P[a_t]} \\ &= \frac{1}{P[a_t]} \left[P[E_t, \rho_t | a_t, E_{t-1}] P[a_t | E_{t-1}] P[E_{t-1}] \right. \\ &\quad \left. + \, P[E_t, \rho_t | a_t, E_{t-1}^c] P[a_t | E_{t-1}^c] P[E_{t-1}^c] \right] \\ &= \frac{1}{P[a_t]} \left[p_{on}(\gamma_1\rho_1 + \gamma_2\rho_2) P[a_t, E_{t-1}] \right. \\ &\quad \left. + \, (1 - p_{off})(\gamma_1\rho_1 + \gamma_2\rho_2) P[a_t, E_{t-1}^c] \right] \\ &\le p_{on}(\gamma_1\rho_1 + \gamma_2\rho_2) P[E_{t-1}|a_t] \\ &\quad + p_{on}(\gamma_1\rho_1 + \gamma_2\rho_2)(1 - P[E_{t-1}|a_t]) \\ &= p_{on}(\gamma_1\rho_1 + \gamma_2\rho_2) \end{aligned}$$

where the inequality results from the fact that $1 - p_{off} \le p_{on}$ for $0.5 < p_{on}, p_{off} < 1.0$. Thus we also have

$$\bar{P}_S \le p_{on}(\gamma_1\rho_1 + \gamma_2\rho_2) \tag{7}$$

Let $Q_S(t)$ denote the probability that an event occurs in time slot t and a transmission is attempted for it (irrespective of the outcome of the transmission) given that the sensor is alive and let $\bar{Q}_S$ denote the steady-state probability of such events. Following along the lines of the characterization of $P_S(t)$, we have

$$\begin{aligned} Q_S(t) &= P[E_t \mid a_t] \\ &= p_{on} P[E_{t-1}|a_t] + (1 - p_{off}) P[E_{t-1}^c|a_t] \\ &\le p_{on} P[E_{t-1}|a_t] + p_{on}(1 - P[E_{t-1}|a_t]) \\ &= p_{on} \end{aligned}$$

and thus $\bar{Q}_S \le p_{on}$. We denote the available energy at the sensor at the beginning of slot t by L_t and assume that the initial charge in the sensor was L_0. The expected charge level of the sensor at slot T is then given by

$$\begin{aligned} E[L_T] &= L_0 + T_1 \left(\mu_{on} c - \delta_0 - \bar{Q}_S(\gamma_1\delta_1 + \gamma_2\delta_2) \right) \\ &\quad + (T - T_1)\mu_{on} c \\ &\le L_0 - T_1 \left(\delta_0 + p_{on}(\gamma_1\delta_1 + \gamma_2\delta_2) \right) + T\mu_{on} c \end{aligned}$$

Rearranging the terms and using the fact that $E[L_T] \ge 0$ we have

$$\lim_{T\to\infty} \frac{T_1}{T} \le \frac{\mu_{on} c}{\delta_0 + p_{on}(\gamma_1\delta_1 + \gamma_2\delta_2)} \tag{8}$$

As $T \to \infty$, the number of event occurrences in the interval $[0, T]$ satisfies

$$\lim_{T\to\infty} \frac{\mathcal{E}_o(T)}{T} = \pi_{on} = \frac{1 - p_{off}}{2 - p_{on} - p_{off}} \tag{9}$$

Combining Eqns. (6), (8) and (9) we have

$$\begin{aligned} U(\Pi_{OPT}) &= \lim_{T\to\infty} \frac{\mathcal{E}_d(T)}{\mathcal{E}_o(T)} = \frac{\bar{P}_S}{\pi_{on}} \lim_{T\to\infty} \frac{T_1}{T} \\ &\le \left(\frac{1}{\pi_{on}} \right) \frac{p_{on}(\gamma_1\rho_1 + \gamma_2\rho_2)\mu_{on} c}{\delta_0 + p_{on}(\gamma_1\delta_1 + \gamma_2\delta_2)} \\ &\le \left(\frac{1}{\pi_{on}} \right) \frac{p_{on}\rho_1\mu_{on} c}{\delta_0 + p_{on}\delta_2} \end{aligned} \tag{10}$$

IV. Markov Decision Process Formulation

The solution to the problem of assigning the transmission mode for each communication event so that the quality of coverage is maximized can be also obtained by formulating it as a Markov Decision Process. This section models the policy assignment problem as a Markov Decision Process.

Denote the system state at time t by $X_t = (L_t, E_t, Y_t)$ where $L_t \in \{0, 1, 2, \cdots\}$ represents the energy available in the sensor at time t, $E_t \in \{0, 1\}$ equals one if an event to be reported occurred at time t and zero otherwise. Also, $Y_t \in \{0, 1\}$ equals one if the sensor is being charged at time t and zero otherwise. The action taken at time t is denoted by $a_t \in \{0, 1, 2\}$ where $a_t = 0$ corresponds to no transmission, $a_t = 1$ corresponds to a transmission using transmission mode 1 and $a_t = 2$ corresponds to a transmission using transmission mode 2.

The next state of the system depends only on the current state and the action taken. Thus the system constitutes a Markov Decision Process. The sensor gains a reward of one with probability ρ_1 if $E_t = 1$ and $a_t = 1$ and a reward of one with probability ρ_2 if $E_t = 1$ and $a_t = 2$. The reward function is then given by

$$r(X_t, a_t) = \begin{cases} p_{on}\rho_1 & \text{if } a_t = 1,\ L_t \geq \delta_0 + \delta_1 \\ & \text{and } E_{t-1} = 1 \\ p_{on}\rho_2 & \text{if } a_t = 2,\ L_t \geq \delta_0 + \delta_2 \\ & \text{and } E_{t-1} = 1 \\ (1 - p_{off})\rho_1 & \text{if } a_t = 1,\ L_t \geq \delta_0 + \delta_1 \\ & \text{and } E_{t-1} = 0 \\ (1 - p_{off})\rho_2 & \text{if } a_t = 2,\ L_t \geq \delta_0 + \delta_2 \\ & \text{and } E_{t-1} = 0 \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

Let g_t and l_t be the amount of energy gained and lost by the sensor in the interval $[t, t+1)$ respectively. Then

$$g_t = \begin{cases} c & \text{w.p. } Y_t q_{on} + (1 - Y_t)(1 - q_{off}) \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

$$l_t = \begin{cases} \delta_0 + \delta_1 & \text{w.p. } [E_t p_{on} + (1 - E_t)(1 - p_{off})] I_1(a_t) \\ & \quad \text{if } L_t \geq \delta_0 + \delta_1 \\ \delta_0 + \delta_2 & \text{w.p. } [E_t p_{on} + (1 - E_t)(1 - p_{off})] I_2(a_t) \\ & \quad \text{if } L_t \geq \delta_0 + \delta_2 \\ \delta_0 & \text{w.p. } I_0(a_t) \text{ if } L_t \geq \delta_0 + \delta_2 \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

where w.p. stands for “with probability”, $I_A(a_t)$ represents the indicator function that equals one only when $a_t = A$ and zero otherwise. To complete the MDP formulation, the next state of the system $X_{t+1} = (L_{t+1}, E_{t+1}, Y_{t+1})$ is given by

$$L_{t+1} = L_t + g_t - l_t \tag{14}$$

$$E_{t+1} = \begin{cases} 1 & \text{w.p. } E_t p_{on} + (1 - E_t)(1 - p_{off}) \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

TABLE I

Optimal Actions when $\delta_0 = 1$, $\delta_1 = 2$, $\delta_2 = 1$, $c = 2$, $\rho_1 = 0.9$, $\rho_2 = 0.6$, $p_{on} = 0.7$ and $p_{off} = 0.9$.

$q_{on} = 0.6$, $q_{off} = 0.7$

$a = 0$	$a = 1$	$a = 2$
$(L, 0, Y)$	$(L, 1, 0)$:$L \geq 5$	$(L, 1, Y)$: $L = 2$
$(L, 1, Y)$:$L < 2$	$(L, 1, 0)$:$L = 3$	$(L, 1, 0)$: $L = 4$
	$(L, 1, 1)$:$L \geq 3$	

$q_{on} = 0.8$, $q_{off} = 0.6$

$a = 0$	$a = 1$	$a = 2$
$(L, 0, Y)$	$(L, 1, Y)$:$L \geq 3$	$(L, 1, Y)$: $L = 2$
$(L, 1, Y)$:$L < 2$		

$$Y_{t+1} = \begin{cases} 1 & \text{w.p. } Y_t q_{on} + (1 - Y_t)(1 - q_{off}) \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

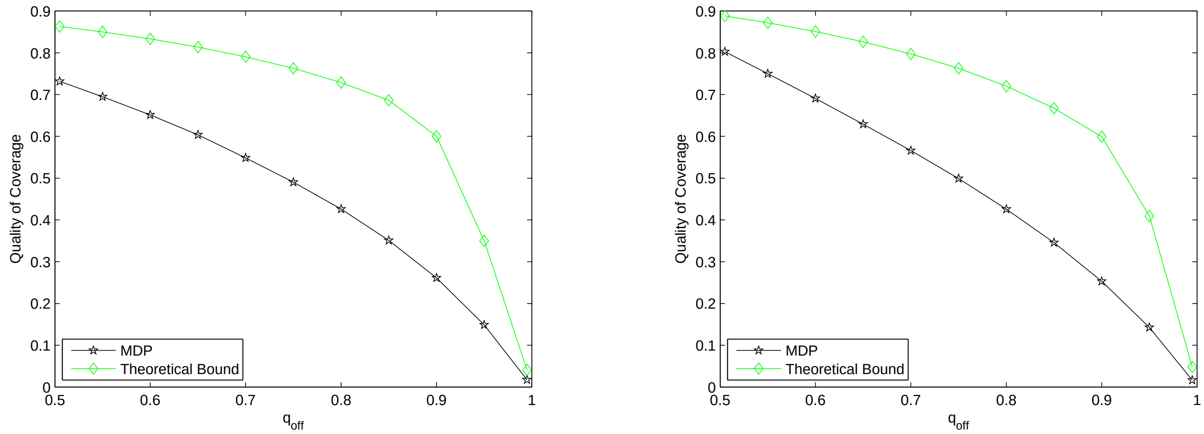
The optimal solution can be computed by using the well known value iteration technique [10]. The battery capacity of the sensor is assumed to be K. Since the induced Markov chain is unichain, from Theorem 8.5.2 of [10], there exists a deterministic, Markov, stationary optimal policy Π_{MD} which also leads to a steady-state transition probability matrix. Considering the average expected reward criteria, the optimality equations are given by [2]

$$h^*(X) = \max_{a \in \{0,1,2\}} \left[r(X, a) + \lambda^* + \sum_{X'=(0,0,0)}^{(K,1,1)} p_{X,X'}(a) h^*(X') \right]$$
$$\forall X \in \{(0, 0, 0), \cdots, (K, 1, 1)\} \tag{17}$$

where $p_{X,X'}(a)$ represents the transition probability from state X to X' when action a is taken, λ^* is the optimal average reward and $h^*(i)$ are the optimal rewards when starting at state $i = (0, 0, 0), \cdots, (K, 1, 1)$. For the purpose of evaluation, the relative value iteration technique [2] is used to solve Eqn. (17). Table I shows the optimal policy for two values of the recharge rate. The optimal policy roughly corresponds to using transmission mode 2 when the battery charge is low and switching to transmission mode 1 when the battery charge increases.

V. Simulation Results

In this section we use simulation results to compare the performance of of the three strategies and also to evaluate the impact of various system parameters on the performance. The simulations were done using a custom built simulator written in C. All simulations were run for



(a) $p_{on} = 0.6$, $\rho_2 = 0.4$, $\frac{\rho_1}{\delta_1} > \frac{\rho_2}{\delta_2}$

(b) $p_{on} = 0.7$, $\rho_2 = 0.6$, $\frac{\rho_1}{\delta_1} \leq \frac{\rho_2}{\delta_2}$

Fig. 1. Comparison of the quality of coverage of the three policies. Parameters used: $q_{on} = 0.75$, $p_{off} = 0.9$, $c = 2$, $\rho_1 = 0.9$, $\delta_0 = 1$, $\delta_1 = 2$ and $\delta_2 = 1$.

a duration of 5000000 time units.

Figure 1 compares the performance of the Markov Decision Process based strategy (labeled MDP) in terms of the quality of coverage U as the recharge rate is varied by changing q_{off}. Two scenarios corresponding to $\frac{\rho_1}{\delta_1} \leq \frac{\rho_2}{\delta_2}$ and $\frac{\rho_1}{\delta_1} > \frac{\rho_2}{\delta_2}$ are considered.

Next, we explore the impact of various system parameters on the performance of the communication strategies. For purposes of illustration, we show the results for the MDP based policy and the other policies follow the same trend. In Figure 2(a) we explore the effect of the recharge process on the performance. Note that as q_{on} (q_{off}) increases, μ_{on} (μ_{off}) as well as the average length of a recharge (non-recharge) period increases. While the performance improves as q_{on} increases or q_{off} decreases, q_{on} has a greater impact on the performance. Figure 2(b) compares the performance of the MDP based strategy for the two cases of $\frac{\rho_1}{\delta_1} \leq \frac{\rho_2}{\delta_2}$ and $\frac{\rho_1}{\delta_1} > \frac{\rho_2}{\delta_2}$ for different values of q_{on} and q_{off}. We note that the performance in the case where $\frac{\rho_1}{\delta_1} > \frac{\rho_2}{\delta_2}$ increases faster as q_{on} increases. This is because a larger q_{on} increases the amount of charge available and thus allows more transmissions using transmission mode 1 that is preferred in this case. A similar trend can be inferred from Figure 3 which evaluates the impact of p_{on} and p_{off} on the performance.

VI. Conclusions

Body sensor networks have the potential to significantly improve the quality of many medical and non-medical applications and services by facilitating the real time monitoring of human activity and body functions. To facilitate the development of communication technology to assist in the deployment of such networks, this paper addressed the problem of developing transmission strategies for BSNs when energy harvesting devices are used by the sensors to generate energy. Three strategies for scheduling transmissions at different energy consumption levels are considered and theoretical upper and lower bounds are obtained on the achievable performance. Simulation results show that while a strategy based on a Markov Decision Process has better quality of coverage that both energy balancing and aggressive policies. In certain scenarios, the energy balancing policy may outperform the other two in terms of the number of dead slots and the average number of consecutive messages that are not reported correctly.

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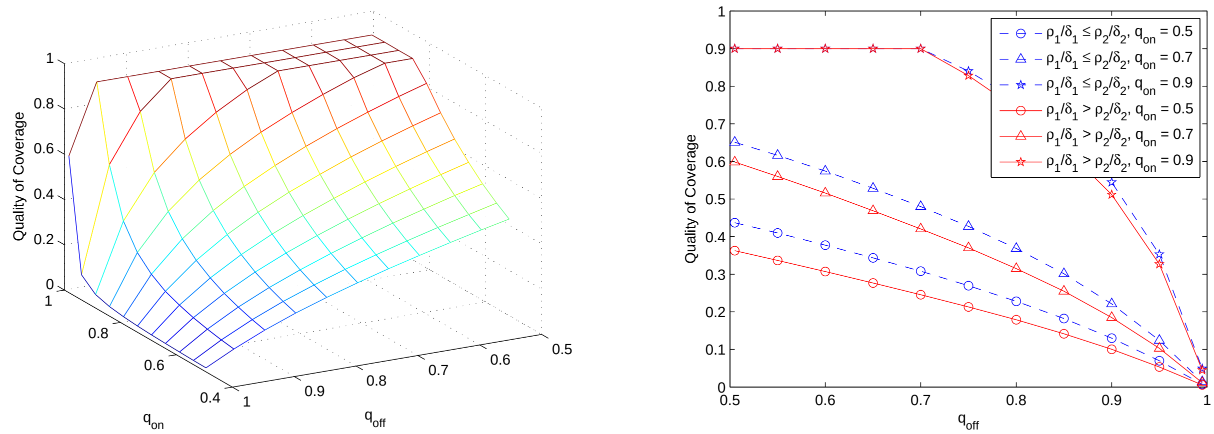
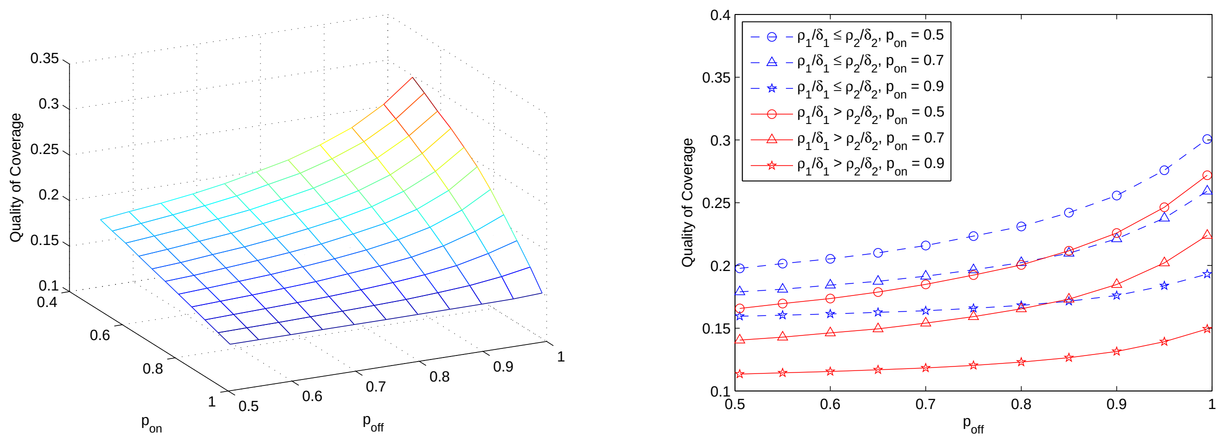


(a) $\rho_1 = 0.9,\ \rho_2 = 0.6,\ \frac{\rho_1}{\delta_1} \leq \frac{\rho_2}{\delta_2}$ (b) $\{\rho_1 = 0.9, \rho_2 = 0.6\}$ and $\{\rho_1 = 0.9, \rho_2 = 0.4\}$

Fig. 2. Effect of q_{on} and q_{off} on the quality of coverage for the MDP based strategy. Parameters used: $p_{on} = 0.7$, $p_{off} = 0.9$, $c = 2$, $\delta_0 = 1$, $\delta_1 = 2$ and $\delta_2 = 1$.



(a) $\rho_1 = 0.9,\ \rho_2 = 0.6,\ \frac{\rho_1}{\delta_1} \leq \frac{\rho_2}{\delta_2}$ (b) $\{\rho_1 = 0.9, \rho_2 = 0.6\}$ and $\{\rho_1 = 0.9, \rho_2 = 0.4\}$

Fig. 3. Effect of p_{on} and p_{off} on the quality of coverage for the MDP based strategy. Parameters used: $q_{on} = 0.7$, $q_{off} = 0.9$, $c = 2$, $\delta_0 = 1$, $\delta_1 = 2$ and $\delta_2 = 1$.

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