

# On Outage Probability for Stochastic Energy Harvesting Communications in Fading Channels

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**Abstract**—An optimal transmission policy is considered for energy harvesting (EH) wireless point-to-point communications, wherein the source node is solar-powered and equipped with a finite-sized battery. The long-term outage probability is minimized by adapting the transmission power to the causal energy arrival information, battery energy amount and channel fading through a Markov decision process (MDP) framework. We reveal an interesting saturated structure of the expected outage probability for which it eventually converges to a battery empty probability in high signal-to-noise power ratio (SNR). This phenomenon that links outage probability with EH capability is derived based on a monotonic and bounded differential structure of the long-term reward and a threshold structure of the optimal policy. Furthermore, a saturation-free condition on the outage performance is presented as well. Simulations confirm the theoretical analysis and the superiority of the proposed policy.

**Index Terms**—Markov decision process, outage probability, stochastic energy harvesting.

## I. INTRODUCTION

RECENTLY, energy harvesting (EH) communications have attracted more and more attentions due to their effectiveness in solving the energy supply problems in wireless networks without grid power supply [1]. Because of the randomness and uncertainty of the energy harvested from environment, unwise power allocation schemes may degrade the system performance dramatically. Thus, it is a crucial research issue to optimize the performance by adapting the power allocation to not only the channel dynamics but also the random energy.

EH communications have been studied in point-to-point scenarios in the literature. Regarding to the throughput maximization, the work in [2] proposed optimal power scheduling for maximizing the short-term throughput in fading channels by utilizing a deterministic EH model, in which the solar energy state information (ESI) is non-causal and the energy profile is known prior to transmission scheduling, and a stochastic EH

model, in which the solar ESI is causal. In [3], an optimal transmission policy was analyzed to maximize the finite-horizon throughput for EH transmitters with the consideration of circuit power. Moreover, the authors in [4] investigated a data-driven stochastic EH model wherein underlying parameters are directly estimated by a real data record of solar irradiance, and then an optimal transmission policy was proposed to maximize the long-term net bit rate. Regarding with the outage probability minimization, the outage performance loss incurred by different EH rates was analyzed in [5], based on a special EH circuit model with a main and a secondary energy storage devices. References [6] and [7] proposed optimal power scheduling to minimize the upper bound of the outage probability over a finite horizon. In [8], the optimal power allocation scheme that aims at minimizing the outage probability over a finite horizon was also studied under both deterministic and stochastic EH models. The authors in [9] intended to minimize the data packet outage probability for an EH transmitter and an EH receiver in a fading channel. However, the optimal transmission power policy for minimizing the long-term outage probability has not been studied with respect to stochastic EH models. Furthermore, the impact of the randomness of harvested energy on the characteristic of the outage performance has not yet been thoroughly analyzed.

Motivated by the above discussions, we utilize the stochastic EH model in [4] and propose an optimal transmission policy for the point-to-point wireless link, where the source node is solar-powered and equipped with a finite-capacity battery. Our goal is to minimize the long-term outage probability of the wireless link by adapting the transmission power to the system conditions, including the causal solar ESI, battery energy and channel fading, through an Markov decision process (MDP) framework. Most importantly, we find an interesting saturated structure for the outage performance, in that the outage probability eventually approaches to the battery empty probability in high signal-to-noise power ratio (SNR) regimes. To obtain this important result that links outage probability with EH capability, we uncover a threshold structure of the optimal policy, which is derived based on a monotonic and bounded differential structure of the long-term outage probability. Finally, a saturation-free condition is proposed to guarantee the outage probability going to zero in high SNRs.

## II. SYSTEM MODEL AND MARKOV DECISION PROCESS

Consider a point-to-point wireless link, where a solar-powered source node with a finite-sized battery intends to communicate with its destination node. We assume that the wireless channel is quasi-static and Rayleigh flat fading with average channel power  $\theta$ . Further, the source node has the perfect knowledge of the channel state information (CSI). Our objective is to

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minimize the long-term outage probability of the point-to-point link by adapting the transmission power of the EH source node to the battery energy amount, CSI and causal solar ESI. The problem is solved via an MDP model, the main components of which include states, actions and a reward function, corresponding to the system conditions, the transmission power and the outage probability, respectively.

#### A. Transmission Power Action

Let  $\mathcal{A} = \{0, 1, \dots, N_p - 1\}$  denote a transmission power action set of the source node. When the action  $A = a \in \mathcal{A}$  is taken, the transmission power  $P$  is set as  $aP_u$  during one transmission period  $T$ , where  $P_u$  is the basic transmission power with respect to one energy quantum  $E_u$  during the period  $T$ , i.e.,  $E_u = P_u T$ . Particularly, if  $a = 0$ , it represents that the source node keeps silent.

#### B. System States

Let  $\mathcal{S} = \mathcal{Q}_e \times \mathcal{Q}_c \times \mathcal{Q}_b$  be a three-tuple state space, where  $\times$  denotes the Cartesian product,  $\mathcal{Q}_e = \{0, 1, \dots, N_e - 1\}$ ,  $\mathcal{Q}_c = \{0, 1, \dots, N_c - 1\}$  and  $\mathcal{Q}_b = \{0, 1, \dots, N_b - 1\}$  denote a solar EH state set, a channel state set and a finite-sized battery state set, respectively. Moreover, a notation  $S = (Q_e, Q_c, Q_b) \in \mathcal{S}$  is defined for the stochastic state of the MDP. The detailed discussion is as follows.

(a) *Solar EH State:* An  $N_e$ -state stochastic EH model in [4] is exploited to mimic the evolution of the solar EH conditions. Unlike the traditional Markov model [10], [11] this stochastic EH model is a real-data-driven Markov chain, and its underlying parameters are trained by exploiting the solar irradiance data record in [12]. It is assumed that different solar EH states represent different solar irradiance intensities, and the dynamic of the states is governed by a state transition probability  $P(Q_e = e' | Q_e = e)$ , for  $\forall e, e' \in \mathcal{Q}_e$ .

If the solar EH state is given by  $Q_e = e \in \mathcal{Q}_e$ , the harvested solar power per unit area,  $P_h$ , is a Gaussian-distributed random variable with  $\mathcal{N}(\mu_e, \rho_e)$ . Since every measurement data in [12] is the average value of the harvested solar power in one period  $T$ , we assume that the solar EH condition is quasi-static during one period  $T$ . Thus, the random solar energy harvested during  $T$  can be computed as  $E_h = P_h T \Omega \eta$ , where  $\eta$  denotes an energy conversion efficiency and  $\Omega$  is a solar panel area. Further, a quantization model is used to deal with the harvested energy, which is quantized in units of  $E_u$ , and then stored in the battery for the forthcoming data transmission [13]. Let the random variable  $Q$  denote the number of harvested energy quanta. The probability distribution of  $Q$  conditioned on the  $e$ th solar EH state, denoted as  $P(Q = q | Q_e = e) (\forall e \in \mathcal{Q}_e, q \in \{0, 1, \dots, \infty\})$ , and the relationship among  $E_h$ ,  $E_u$  and  $Q$  are theoretically derived in [4].

(b) *Battery State:* The battery is uniformly quantized into several levels in units of  $E_u$ . For  $Q_b = b \in \mathcal{Q}_b$ , the available energy in the battery is given by  $bE_u$ . The battery state transition can be expressed as

$$b' = b - a + q, \quad (1)$$

where  $a$  is the power action,  $q$  denotes the number of harvested energy quanta,  $b$  and  $b'$  represent the current and next battery states, respectively. According to the energy *harvest-store-use* model [2], [3], [13], we assume that the harvested energy in the

current period can only be used for data transmission in the next period, and thus it implies that  $a \leq b$ . In addition, the battery state transition probability at the  $e$ th solar EH state for the power action  $a$  can be expressed as  $P_a(Q_b = b' | Q_b = b, Q_e = e)$  [4].

(c) *Channel States:* The instantaneous channel power  $\gamma$  is quantized into  $N_c$  levels via a finite number of thresholds  $\Gamma = \{0 = \Gamma_0, \Gamma_1, \dots, \Gamma_{N_c} = \infty\}$ . For  $Q_c = c \in \mathcal{Q}_c$ , it means the channel power  $\gamma$  belongs to the interval  $[\Gamma_c, \Gamma_{c+1})$ . Besides, the channel transition from one level to another is formulated by a finite-state Markov chain. By assuming that the channel varies slowly and can only transit from the current state to its neighboring states, the channel state transition probability  $P(Q_c = c' | Q_c = c)$ , for  $\forall c \in \mathcal{Q}_c$ ,  $c' \in \{\max(0, c-1), \dots, \min(c+1, N_c-1)\}$ , is defined in [14].

(d) *MDP State Transition:* Since the solar irradiance and the channel fading are independent of each other, the system state transition probability from the state  $s = (e, c, b)$  to the state  $s' = (e', c', b')$  for the action  $A = a$  can be computed as

$$P_a(s' | s) = P(Q_e = e' | Q_e = e) \cdot P(Q_c = c' | Q_c = c) \cdot P_a(Q_b = b' | Q_b = b, Q_e = e). \quad (2)$$

#### C. Reward Function

Let  $N_0$  be the destination noise power. The reward function is defined as the conditional outage probability of the point-to-point fading channel with respect to the state  $s = (e, c, b)$  and the action  $a$ , given by

$$R_a(s) \triangleq P_{out}(c, a) = \Pr \left\{ \log \left( 1 + \frac{\gamma P}{N_0} \right) < R_{th} | Q_c = c, P = aP_u \right\} = \Pr \{ \gamma < \gamma_{th} | \Gamma_c \leq \gamma < \Gamma_{c+1} \}, \quad (3)$$

where  $R_{th}$  is the target rate and  $\gamma_{th} = \frac{N_0}{aP_u} (2^{R_{th}} - 1)$ . Then, the reward function is computed by discussing the relationship among  $\gamma_{th}$ ,  $\Gamma_c$  and  $\Gamma_{c+1}$  in the following three cases:

- Case 1 ( $\gamma_{th} \geq \Gamma_{c+1}$ ):  $R_a(s) = 1$ ;
- Case 2 ( $\gamma_{th} \leq \Gamma_c$ ):  $R_a(s) = 0$ ;
- Case 3 (Otherwise): It can be derived that

$$R_a(s) = \frac{\Pr \{ \Gamma_c \leq \gamma < \min(\Gamma_{c+1}, \gamma_{th}) \}}{\Pr \{ \Gamma_c \leq \gamma < \Gamma_{c+1} \}} = \frac{e^{-\Gamma_c/\theta} - e^{-\min(\gamma_{th}, \Gamma_{c+1})/\theta}}{e^{-\Gamma_c/\theta} - e^{-\Gamma_{c+1}/\theta}}.$$

Especially, the reward functions when the source keeps silent or in case of sufficiently high SNRs are degenerated to:

$$\begin{cases} R_{a=0}(s) = P_{out}(c, a=0) = 1; \\ \lim_{N_0 \rightarrow 0, a \geq 1} R_a(s) = \lim_{N_0 \rightarrow 0, a \geq 1} P_{out}(c, a) = 0. \end{cases} \quad (4)$$

#### D. Optimization of Transmission Policy

Define  $\pi(s) : \mathcal{S} \rightarrow \mathcal{A}$  as a policy that specifies the source transmission power action. The goal of the MDP is to find the optimal  $\pi^*(s)$  at the state  $s$  to minimize the long-term outage probability:

$$V_\pi(s_0) = \mathbb{E}_\pi \left[ \sum_{k=0}^{\infty} \lambda^k R_{\pi(s_k)}(s_k) \right], s_k \in \mathcal{S}, \pi(s_k) \in \mathcal{A}, \quad (5)$$

where  $s_0$  is the initial state and  $\lambda \in [0, 1)$  is a discount factor. The optimal policy can be found through the Bellman equation [15], which can be solved by executing the value iterations

$$\begin{cases} V_a^{(i+1)}(s) = R_a(s) + \lambda \sum_{s' \in \mathcal{S}} P_a(s'|s) V^{(i)}(s'), \\ V^{(i+1)}(s) = \min_{a \in \mathcal{A}} \left( V_a^{(i+1)}(s) \right), \end{cases} \quad (6)$$

where  $s \in \mathcal{S}$ ,  $a \in \mathcal{A}$ ,  $i$  is the iteration number, and the initial value  $V_0(s)$  is set as zero for all states. Since the different states are independent, for simplicity, the summation term in (6) can be rewritten as an expectation form in (7) by applying (2) and the change of variable, wherein  $\mathbb{E}_{e,c,b}[\cdot]$  takes the expected value with respect to  $s'$  conditioned on  $s$  (see (7) at the bottom of the page).

### III. STRUCTURE OF OPTIMAL TRANSMISSION POLICY

In this section, we first introduce a monotonic and bounded differential structure of the long-term reward as follows.

*Proposition 1:* For any fixed system state  $s = (e, c, b > 0) \in \mathcal{S}$  in the  $i$ th value iteration, the expected long-term reward is non-increasing in the battery state, and the differential value of the expected long-term rewards for two adjacent battery states is not larger than one, i.e.,  $1 \geq V^{(i)}(e, c, b-1) - V^{(i)}(e, c, b) \geq 0, \forall b \in \mathcal{Q}_b \setminus \{0\}$ . Moreover, the optimal policy  $\pi^*$  is also satisfied with the above special structure, i.e.,  $1 \geq V_{\pi^*}(e, c, b-1) - V_{\pi^*}(e, c, b) \geq 0, \forall b \in \mathcal{Q}_b \setminus \{0\}$ .

*Proof:* We can utilize the induction method to prove this proposition. The conclusion and the proof of this proposition are similar to those of Lemma 1 and Theorem 1 in [4], except for two different points. The first is that the expected long-term reward is non-increasing in the battery state, rather than non-decreasing. This is because our objective is minimizing the long-term reward in (6). The second is that the long-term reward is restricted to the bounded differential structure, since the immediate reward, i.e., the conditional outage probability, inherently ranges between 0 and 1. Thus, it can be obtained from the induction that the differential value of the long-term rewards for two adjacent battery states is bounded by one. ■

Now we turn to analyze the structure of the optimal policy.

*Proposition 2:* In sufficiently high SNRs, the optimal transmission policy  $\pi^*$  has a threshold structure, which means the optimal transmission power action  $a^*$  is equal to 0 when the battery state  $b = 0$ , and  $a^*$  is equal to 1 when  $b > 0$ .

*Proof:* The proposition can be proved by considering the battery state in the following three cases.

- Case 1 ( $b = 0$ ): Since the battery is empty, the accessible power action is only  $a = 0$ .
- Case 2 ( $b = 1$ ): For any iteration  $i$  and system state  $s = (e, c, b > 0) \in \mathcal{S}$ , according to (4), (6) and (7), the value difference of the two long-term rewards for the power action  $a = 1$  and  $a = 0$  in sufficiently high SNRs can be calculated as (8). From Proposition 1, the expectation

term in (8) takes a value ranging between 0 and 1. Since  $0 < \lambda < 1$ , we get

$$\begin{aligned} \lim_{N_0 \rightarrow 0} \left[ V_{a=1}^{(i+1)}(s) - V_{a=0}^{(i+1)}(s) \right] &= -1 + \lambda \cdot \lim_{N_0 \rightarrow 0} \mathbb{E}_{e,c,b} \\ &\times \left[ V^{(i)}(e', c', \min(b-1+q, N_b-1)) \right. \\ &\left. - V^{(i)}(e', c', \min(b+q, N_b-1)) \right]. \end{aligned} \quad (8)$$

$$\lim_{N_0 \rightarrow 0} V_{a=1}^{(i+1)}(e, c, b) < \lim_{N_0 \rightarrow 0} V_{a=0}^{(i+1)}(e, c, b). \quad (9)$$

By applying (6), the optimal power action in iteration  $i+1$  is  $a^* = 1$ . Once the value iteration algorithm is converged, the optimal power action is also given by  $a^* = 1$ .

- Case 3 ( $b \geq 2$ ): Consider a power action  $a = x$  that satisfies the condition  $b \geq x > 1$ . From (4), (6) and (7), the value difference between  $V_{a=x}^{(i+1)}(s)$  and  $V_{a=1}^{(i+1)}(s)$  in sufficiently high SNRs can be written as (10). By applying Proposition 1, it can be shown that

$$\begin{aligned} \lim_{N_0 \rightarrow 0} \left[ V_{a=x}^{(i+1)}(s) - V_{a=1}^{(i+1)}(s) \right] &= \lambda \cdot \lim_{N_0 \rightarrow 0} \mathbb{E}_{e,c,b} \\ &\times \left[ V^{(i)}(e', c', \min(b-x+q, N_b-1)) \right. \\ &\left. - V^{(i)}(e', c', \min(b-1+q, N_b-1)) \right]. \end{aligned} \quad (10)$$

$$\lim_{N_0 \rightarrow 0} V_{a=x}^{(i+1)}(e, c, b) > \lim_{N_0 \rightarrow 0} V_{a=1}^{(i+1)}(e, c, b). \quad (11)$$

Notice that for this case, the inequality (9) also holds. From (9), (11) and the value iteration algorithm in (6), the optimal power action is given by  $a^* = 1$ .

Considering all the three cases, we can conclude that the optimal power action  $a^* = 0$  when  $b = 0$ , and  $a^* = 1$  when  $b > 0$  in high SNR regimes. ■

### IV. PERFORMANCE ANALYSIS OF OUTAGE PROBABILITY

For a given policy  $\pi(s)$ , we can easily calculate the corresponding steady state probability  $p_{\pi(s)}(s)$  by using the transition probability in (2) and balance equations [4]. The expected outage probability is then calculated by taking expectation over the reward function using the steady state probability:

$$\bar{R} = \sum_{s \in \mathcal{S}} p_{\pi(s)}(s = (e, c, b)) \times R_{\pi(s)}(s = (e, c, b)). \quad (12)$$

Based on the developed structures of our optimal policy, we obtain the main result of this paper, i.e., there exists a saturated structure for the expected outage probability.

*Theorem 1:* In sufficiently high SNRs, the expected outage probability for the proposed optimal policy  $\pi^*$  is equal to the battery empty probability  $P_{\pi^*}(b = 0)$ .

*Proof:* By considering the battery state, the expected reward can be rewritten as

$$\bar{R} = \sum_{s \in \mathcal{S}} [p_{\pi^*}(e, c, b=0) + p_{\pi^*}(e, c, b \geq 1)] R_{\pi^*}(e, c, b \geq 1). \quad (13)$$

$$\begin{aligned} \sum_{s' \in \mathcal{S}} P_a(s'|s) V^{(i)}(s') &= \sum_{e', c'} P(Q_e = e' | Q_e = e) P(Q_c = c' | Q_c = c) \\ &\cdot \sum_{q=0}^{\infty} P(Q = q | Q_e = e) \cdot V^{(i)}(e', c', \min(b-a+q, N_b-1)) = \mathbb{E}_{e,c,b} \left[ V^{(i)}(e', c', \min(b-a+q, N_b-1)) \right], \end{aligned} \quad (7)$$

From Proposition 2, the optimal action in sufficiently high SNRs is given by  $\pi^*(e, c, b > 0) = 1$ . From (4), the expected outage probability in high SNRs is expressed as

$$\lim_{N_0 \rightarrow 0} \bar{R} = \sum_{e \in \mathcal{Q}_e} \sum_{c \in \mathcal{Q}_c} p_{\pi^*}(e, c, b = 0) = P_{\pi^*}(b = 0), \quad (14)$$

where  $P_{\pi^*}(b = 0)$  represents the battery empty probability with respect to the optimal policy  $\pi^*$ . ■

In the following, we discuss the saturation-free condition.

**Definition 1:** (Energy Deficiency Probability) It is the probability in case of the number of harvested energy quanta is equal to zero, conditioned on the solar EH state, i.e.,  $P(Q = 0 | Q_e = e), \forall e \in \mathcal{Q}_e$ .

**Theorem 2:** The expected outage probability for the proposed optimal policy  $\pi^*$  approaches to zero in sufficiently high SNRs, if and only if the energy deficiency probability is equal to zero, i.e.,  $P(Q = 0 | Q_e = e) = 0, \forall e \in \mathcal{Q}_e$ .

*Proof:* From Theorem 1 and (1), if the expected outage probability is saturation-free, the battery empty probability  $P(b = 0)$  must be equal to zero, i.e., the battery state in the  $t^{\text{th}}$  ( $\forall t \geq 1$ ) period  $b_t = b_{t-1} - a_t^* + q_t \geq 1$ , where  $a_t^*$  and  $q_t$  denote the optimal action and the number of harvested energy quanta, respectively. According to Proposition 2,  $a_t^*$  is equal to 1 in high SNR regimes, and the above condition can be equivalently rewritten as  $q_t \geq 2 - b_{t-1}, \forall t$ . Because the battery must be non-empty, i.e.,  $b_{t-1} \geq 1$ , this condition implies that the outage probability is saturation-free only if  $q_t \geq 1 (\forall t)$ , i.e., the energy deficiency probability is equal to zero.

On the other side, if  $P(Q = 0 | Q_e = e) = 0, \forall e \in \mathcal{Q}_e$ , it means that the source node can harvest at least one energy quantum in every transmission period, and thus the battery empty probability is equal to zero. By applying Theorem 1, the expected outage probability approaches to zero in high SNRs. Hence, the proposition is proved. ■

## V. SIMULATION RESULTS

In this section, the outage probability of our proposed optimal policy based on the stochastic EH model in [4] is evaluated by computer simulations. The analytical results are calculated according to (12), while the simulation results are computed using the Monte-Carlo method. The numbers of the solar EH states, channel states and battery states are four, six and twelve, respectively. The solar irradiance measurements are taken at five minute intervals, and the solar energy conversion efficiency is  $\eta = 20\%$ . The channel is quantized as  $\Gamma = \{0, 0.3, 0.6, 1.0, 2.0, 3.0, \infty\}$  with the average channel power  $\theta = 1$ , and the channel gain is generated using Jakes' model [16]. The transmission period is set as  $T = 300s$ , and the channel coherence time  $\frac{T}{2f_D}$  for the normalized Doppler frequency  $f_D = 0.05$  is fifty minutes. Thus, the channel remains quasi-static within the transmission period. Meanwhile, the battery state is initialized randomly, and the discount factor is  $\lambda = 0.99$ . A normalized SNR is defined with respect to the transmission power of  $1mW$ .

Fig. 1 demonstrates the outage probabilities of our proposed optimal policy for different solar panel area  $\Omega$  and energy quantum size  $E_u$ . It is seen that the analytical results and simulation results match very well, and there exists the saturated structure, i.e., the outage probability is gradually saturated and finally close to the battery empty probability in high SNR regimes, instead of going to zero. This phenomenon coincides

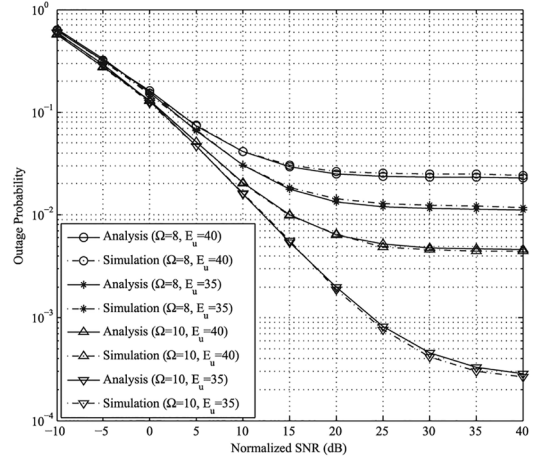


Fig. 1. Outage probabilities for different solar panel area  $\Omega$  and energy quantum  $E_u$  ( $R_{th} = 4bit/s/Hz$ , Unit of  $\Omega$ :  $cm^2$ , Unit of  $E_u$ :  $300mJ$ ).

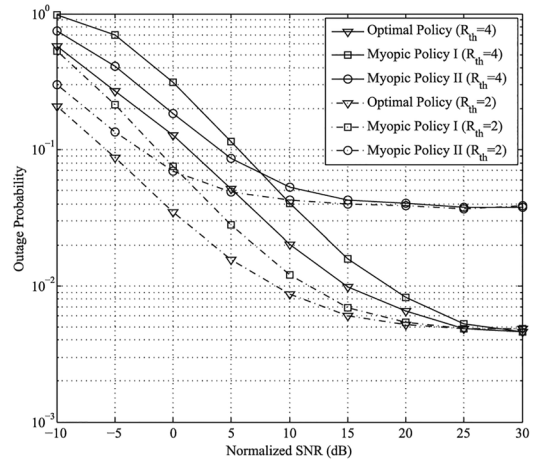


Fig. 2. Outage probabilities for the proposed optimal policy and two myopic policies ( $\Omega = 10cm^2$ ,  $P_u = 40mW$ , Unit of  $R_{th}$ :  $bit/s/Hz$ ).

with Theorem 1. We also observe that the saturation outage probability in high SNR regimes becomes smaller when  $\Omega$  gets larger or  $E_u$  gets smaller. This is due to the fact that more energy quanta can be harvested within one transmission period, and the energy deficiency probability and the battery empty probability  $P_{\pi^*}(b = 0)$  can be reduced by increasing  $\Omega$  or decreasing  $E_u$ .

Fig. 2 compares the outage probabilities of our proposed optimal policy and two myopic policies. For these two myopic policies, the transmission power is set without concern for the system conditions. In Myopic Policy I, the source node merely utilizes the lowest power  $P_u$  for data transmission. Regarding with Myopic Policy II, the source node exploits the largest available energy in the battery during each transmission period. It is seen that the outage probability of our proposed optimal policy outperforms those of the two myopic policies. The performances of these three policies are all saturated in high SNR regimes, and the saturation outage probabilities correspond to their own battery empty probabilities at sufficiently high SNRs. Since the proposed optimal policy is equivalent to Myopic Policy I in high SNR regimes according to Proposition 2, the saturation outage probabilities of these two policies are identical. In Myopic Policy II, its battery empty probability and saturation outage probability are larger than those of the optimal policy. Finally, when the target rate  $R_{th}$  gets smaller, the outage probability becomes better.

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