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 show that the proposed optimal policy is superior to other myopic ones.**

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

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], e.g., wireless sensor networks. 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 arrivals.

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 and the energy arrival is described as a stochastic process. 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. With concern for 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. Reference [6] proposed optimal power scheduling to minimize the upper bound of the average outage probability over a finite horizon. In [7], the optimal power allocation scheme that aims at minimizing the average outage probability over a finite horizon was also studied under both deterministic and stochastic EH models. The authors in [8] 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, especially for a realistic EH model in [4]. 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 aforementioned discussions, we utilize the data-driven 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 expected 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 first 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 θ. Further, the source node has the perfect knowledge of the channel state information (CSI). Our objective is to minimize the long-term outage probability of the point-to-point communication 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. Details are described as follows.

A. Transmission Power Action: Let $\mathcal{A}=\{0,1,\cdots,N_p-1\}$ 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., $E_u=P_uT$. 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, $\mathcal{Q}_e=\{0,1,\cdots,N_e-1\}$, $\mathcal{Q}_c=\{0,1,\cdots,N_c-1\}$ and $\mathcal{Q}_b=\{0,1,\cdots,N_b-1\}$ 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 system stochastic state of the MDP. In the following, we discuss the detailed definition of each state.

(a) Solar EH State: An N_e-state stochastic EH model in [4] is exploited to mimic the evolution of the solar EH conditions. Therein, different solar EH states represent different solar irradiance intensities, and the harvested solar power per unit area, P_h, at the e^{th} solar EH state is assumed to be a Gaussian-distributed random variable with $\mathcal{N}(\mu_e,\rho_e)$. Thus, the random solar energy harvested during one period T can be computed as $E_h=P_hT\Omega\eta$, where Ω is a solar panel area and η denotes an energy conversion efficiency. Through energy quantization, the harvested energy is conveyed to the battery in units of E_u, and the probability of the number of harvested energy quanta conditioned on the e^{th} solar EH state, denoted as $P(E=q|Q_e=e)$ ($\forall e\in\mathcal{Q}_e, q\in\{0,1,\cdots,\infty\}$), is theoretically derived in [4]. Moreover, the dynamic of the states is governed by a state transition probability $P(Q_e=e'|Q_e=e), \forall e,e'\in\mathcal{Q}_e$.

(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. Since the battery state transition is related to both the transmission power action and the number of harvested energy quanta, the battery state transition probability at the e^{th} solar EH state for the power action $a\in\mathcal{A}$ can be expressed as $P_a(Q_b=b'|Q_b=b,Q_e=e)$, which can be computed by using $P(E=q|Q_e=e)$ [4].

(c) Channel States: The instantaneous channel power γ is quantized into N_c levels via a finite number of thresholds $\Gamma=\{0=\Gamma_0,\Gamma_1,\cdots,\Gamma_{N_c}=\infty\}$. For $Q_c=c\in\mathcal{Q}_c$, it means the channel power γ 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 $\forall c\in\mathcal{Q}_c$, $c'\in\{\max(0,c-1),\cdots,\min(c+1,N_c-1)\}$, is defined in [9].

(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

$$\begin{aligned} P_a(s'|s)=&P(Q_e=e'|Q_e=e)\cdot P(Q_c=c'|Q_c=c)\\ &\cdot P_a(Q_b=b'|Q_b=b,Q_e=e). \end{aligned}\tag{1}$$

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 $A=a$, given by

$$\begin{aligned} R_a(s)&\triangleq P_{out}(c,a)\\ &=\Pr\left\{\log\left(1+\frac{\gamma P}{N_0}\right)<R_{th}|Q_c=c,P=aP_u\right\}\\ &=\Pr\left\{\gamma<\gamma_{th}|\Gamma_c\le\gamma<\Gamma_{c+1}\right\}, \end{aligned}\tag{2}$$

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

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

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

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

$$\begin{cases} R_{a=0}(s)=P_{out}(c,a=0)=1;\\ \lim\limits_{N_0\to 0,a\ge 1}R_a(s)=\lim\limits_{N_0\to 0,a\ge 1}P_{out}(c,a)=0. \end{cases}\tag{3}$$

D. Optimization of Transmission Policy: Define $\pi(s):\mathcal{S}\to\mathcal{A}$ 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:

$$V_\pi(s_0)=E_\pi\left[\sum\nolimits_{k=0}^{\infty}\lambda^k R_{\pi(s_k)}(s_k)\right], s_k\in\mathcal{S}, \pi(s_k)\in\mathcal{A},\tag{4}$$

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 [10], which can be efficiently solved by executing the well-known value iterations

$$\begin{cases} V_a^{(i+1)}(s)=R_a(s)+\lambda\sum_{s'\in S}P_a(s'|s)V^{(i)}(s');\\ V^{(i+1)}(s)=\min_{a\in\mathcal{A}}\left(V_a^{(i+1)}(s)\right), \end{cases}\tag{5}$$

$$\begin{aligned} \sum\nolimits_{s'\in S}P_a(s'|s)V^{(i)}(s')=&\sum\nolimits_{e',c'}P(Q_e=e'|Q_e=e)P(Q_c=c'|Q_c=c)\cdot\sum\nolimits_{q=0}^{\infty}P(E=q|Q_e=e)\cdot V^{(i)}(e',c',\min(b-a+q,N_b-1))\\ =&\mathbb{E}_{e,c,b}\left[V^{(i)}(e',c',\min(b-a+q,N_b-1))\right], \end{aligned}\tag{6}$$

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. For simplicity, the summation term in (5) can be rewritten as an expectation form in (6) by applying (1), wherein $\mathbb{E}_{e,c,b}[\cdot]$ takes the expected value conditioned on the system state $s=(e,c,b)$.

III. Structure of Optimal Transmission Policy

In this section, we first introduce a special property of the expected long-term reward, which is named monotonic and bounded differential structure 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 π^* 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 (5). 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 transmission policy.

Proposition 2: In sufficiently high SNRs, the optimal transmission policy π^* 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 (3), (5) and (6), 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 in (7). From Proposition 1, the expectation term in (7) takes a value ranging between 0 and 1. Since $0<\lambda<1$, we get

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

By applying (5), 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 (3), (5) and (6), 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 (8). By applying Proposition 1, it can be shown that

$$\lim_{N_0 \to 0} V_{a=x}^{(i+1)}(e,c,b) > \lim_{N_0 \to 0} V_{a=1}^{(i+1)}(e,c,b). \tag{10}$$

Notice that for this case, the inequality (9) also holds. From (9), (10) and the value iteration algorithm in (5), 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 $p_{\pi(s)}(s=(e,c,b))$ by using the state transition probability in (1) and balance equations [4]. The outage probability is then calculated by taking expectation over the reward function using the steady state probability:

$$\bar{R} = \sum\nolimits_{s \in \mathcal{S}} p_{\pi(s)}(s=(e,c,b)) \times R_{\pi(s)}(s=(e,c,b)). \tag{11}$$

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 $\pi^*(s)$ is equal to the battery empty probability $P_{\pi^*(s)}(b=0)$.

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

$$\bar{R} = \sum\nolimits_{s \in \mathcal{S}} [p_{\pi^*}(e,c,b=0) + p_{\pi^*}(e,c,b \geq 1) R_{\pi^*}(e,c,b \geq 1)]. \tag{12}$$

From Proposition 2, the optimal action in sufficiently high SNRs is given by $\pi^*(e,c,b>0)=1$. According to (3), the reward value is equal to zero for the power action $a>0$ in high SNRs, and thus the expected outage probability in high SNRs is expressed as

$$\lim_{N_0 \to 0} \bar{R} = \sum\nolimits_{e \in \mathcal{Q}_e} \sum\nolimits_{c \in \mathcal{Q}_c} p_{\pi^*}(e,c,b=0) = P_{\pi^*}(b=0), \tag{13}$$

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

In the following, we discuss the saturation-free condition of the expected outage probability.

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., $P(E=0|Q_e=e), \forall e \in \mathcal{Q}_e$.

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

$$\lim_{N_0 \to 0} \left[V_{a=1}^{(i+1)}(s) - V_{a=0}^{(i+1)}(s)\right] = -1 + \lambda \cdot \lim_{N_0 \to 0} \mathbb{E}_{e,c,b}\left[V^{(i)}(e',c',\min(b-1+q, N_b-1)) - V^{(i)}(e',c',\min(b+q, N_b-1))\right]. \tag{7}$$

$$\lim_{N_0 \to 0} \left[V_{a=x}^{(i+1)}(s) - V_{a=1}^{(i+1)}(s)\right] = \lambda \cdot \lim_{N_0 \to 0} \mathbb{E}_{e,c,b}\left[V^{(i)}(e',c',\min(b-x+q, N_b-1)) - V^{(i)}(e',c',\min(b-1+q, N_b-1))\right]. \tag{8}$$

Proof: Without loss of generality, the battery state in the t^{th} period ($t \geq 1$) can be expressed as

$$b_t = b_{t-1} - a_t^* + q_t, \tag{14}$$

where a_t^* and q_t are the optimal power action and the number of harvested energy quanta in the t^{th} period, respectively. From Theorem 1, if the expected outage probability is saturation-free, the battery empty probability $P\,(b=0)$ must be equal to zero, i.e. $b_t = b_{t-1} - a_t^* + q_t \geq 1, \forall t$. 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 $P\,(E=0|Q_e=e)=0, \forall e \in \mathcal{Q}_e$, 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 (11), 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 with the normalized Doppler frequency $f_D = 0.05$ [9]. Meanwhile, the battery state is initialized randomly, the transmission period is set as $T = 300s$, and the discount factor is set as $\lambda = 0.99$. In the simulations, a normalized average SNR is defined with respect to the transmission power of $1\ mW$, and the units of Ω, E_u and R_{th} are given as cm^2, $300\ mJ$ and $bit/s/Hz$, respectively.

Fig. 1 demonstrates the outage probabilities of our proposed optimal policy for different solar panel area Ω 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 with Theorem 1. We also observe that the saturation outage probability in high SNR regimes becomes smaller when the solar panel size Ω gets larger or the energy quantum size 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 $P\,(E=0|Q_e=e)$ and the battery empty probability $P_\pi\,(b=0)$ can be reduced by increasing Ω 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, since all the available energy in the battery is consumed at once, 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.

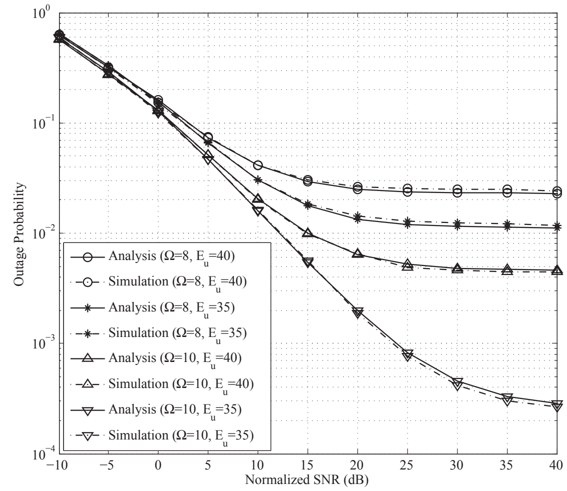

Fig. 1. Outage probabilities for different solar panel area Ω and energy quantum size E_u ($R_{th} = 4\,bit/s/Hz$)

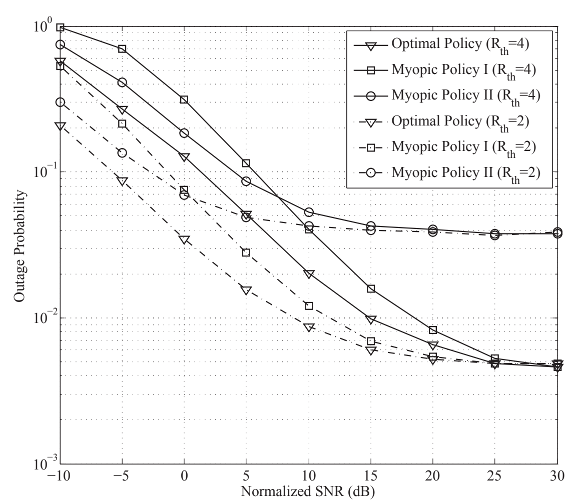

Fig. 2. Outage probabilities for the proposed optimal policy and two myopic policies ($\Omega = 10\,cm^2$ and $P_u = 40\ mW$)

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