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Robust Energy Scheduling for Wireless Communication under Harvesting Uncertainty

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Abstract: In this study, we investigate the energy scheduling problem for wireless communication with energy harvesting devices. We consider wireless transmission systems equipped with energy harvesting devices, which can provide sustainable energy to substitute traditional battery. One of challenging in the system is to efficiently schedule energy consumption to maximize the utility and to adapt to the energy harvesting process. In general, it is difficult to obtain the accurate energy harvesting model parameters. On the other hand, model errors could considerably deteriorate the performances of traditional energy management approaches. We therefore consider robust energy scheduling schemes under the model uncertainty of the energy harvesting process. The problem is formulated as a robust Markov decision process and efficiently solved by robust dynamic programming. Extensive simulation results verify our proposed approaches.

Keywords: Energy harvesting, energy scheduling, robust markov decision process, wireless communication

INTRODUCTION

Energy harvesting technologies (Chao, 2011; Bhuiyan and Dougal, 2010; Hande *et al*., 2010) obtain environmental energy, such as solar power, wind power and vibration, to sustainably provide energy for various applications. It can be used to substitute the traditional batteries, where it is difficult and costly to recharge and replace them. In wireless sensor networks, the limited battery capacity restricts the life-span of sensors and further degrades the performances of these networks. Energy harvesting technologies are promising methods to extend the life-span and improve the performances of sensors (Bhuiyan and Dougal, 2010; Hande *et al*., 2010; Mitcheson *et al*., 2008), which are powered by battery with limited capacity. In this study, we focus on the case that the wireless communication systems are equipped with energy harvesting devices.

One of the challenging in those systems is to design optimal energy scheduling approaches, which can maximize the utility of energy consumption and adapt to the energy harvesting process. Since energy harvesting processes are quite different based on different energy sources, the energy management approaches are required to efficiently manage the harvesting energy. There are a body of works on the energy management approaches for wireless sensor networks (Gladisch *et al*., 2011; Cai *et al*., 2011; Alippi *et al*., 2009; Furthmuller *et al*., 2010). A context-aware energy management system is proposed in the reference (Gladisch *et al*., 2011). In this system, energy budget is determined by energy generation and energy consumption. Moreover, the transmission actions are based on the classified context to keep the energy budget in balance. Cai *et al*. (2011) further considers the unstable availability and capacity of the renewable energy sources and designs the objective to maximize the energy sustainability. In addition, the time-critical application is consider in the reference (Alippi *et al*., 2009). The authors propose an optimal centralized solution for energy management. However, those energy management approaches are based on ideal energy harvesting model and do not consider the uncertainty of the model. Since the model parameters are estimated from limited data, the true harvesting process cannot be accurately predicted. The uncertainty of the harvesting model could considerately deteriorates performances of these approaches. These motivate us to investigate the robust energy management approach to efficiently control energy consumption and energy generation under the uncertainty of the energy harvesting process.

In this study, our main contributions are as follows. First, we propose the framework of the robust energy management problem for wireless communication with energy harvesting devices. We then cast the problem as a

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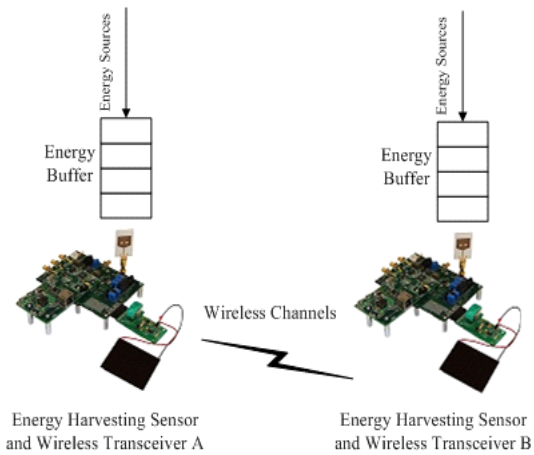

Fig. 1: The energy harvesting system with wireless transceiver modules

robust Markov Decision Process (MDP) (Puterman, 1994) and efficiently solve it via dynamic programming (Bertsekas, 2007). We propose the optimal robust energy management policy, which remains good performance when the energy harvesting process is under uncertainty.

METHODOLOGY

System model: Figure 1 shows the system, which consists of the energy harvesting module and the wireless transceiver module. We consider the point to point wireless communication in the system and assume the time is slotted. All parameters in the system are discretized. The energy harvesting module obtain energy and store it into the energy buffer. Let B_n denote the energy level of the energy buffer in time slot n. We have $0 \le B_n \le C_0$, where C_0 denotes the buffer capacity. Let a_n denote the energy consumption rate in time slot n and H_n denote the energy harvesting rate in time slot n. We assume that a_n and H_n remain stable in time slot n. We have $0 \le a_n \le C_0$, $a_n \in A$ and $0 \le H_n \le H_c$, where H_c denotes the maximum of energy harvesting rate and A is the action set, which is the set of all possible actions. Therefore, the energy level dynamic is given by:

$$B_{n+1} = B_n - a_n T + H_n T \tag{1}$$

where T denotes the length of each time slot. The energy harvesting dynamic is characterized by a Markov chain and its transition probability denoted by $P(H_{n+1}|H_n)$ is independent with a_n. The utility function of energy consumption is given by:

$$U(a_n) = \log_2(1+\Gamma(a_n)) \tag{2}$$

where Γ is the signal-to-noise ratio of the wireless channel. The utility function (2) is the achievable rate according to current transmission power a_n. Let $X_n \triangleq \{B_n, H_n\} \in X$ denote the system state in time slot n, where X is the system state space. The transition probability of system state is given by $P(X_{n+1}|X_{n+1}, a_n)$ and the reward function is given by (2). When the energy harvesting process is given, the nominal energy management problem can be cast as follows:

$$\max_{a_1,\ldots,a_N} E\left\{\sum_{n=1}^{N} U(a_n, X_n)\right\} \tag{3}$$

where, N denotes the total number of time slots and the expectation is over the system state. The objective is to maximize the sum of the utility function over finite time slots. The problem (3) can be solved via dynamic programming. In practice, it is difficult to obtain the accurate transition probability $P(H_{n+1}|H_n)$. However, the error of the transition probability could considerably degrades the performances of the solution in (3). In the next section, we will consider the uncertainty of the energy harvesting process and formulate the robust version of the normal problem (3).

Robust energy management: In practice, the transition probabilities of the energy harvesting process $P(H_{n+1}|H_n)$ are estimated by empirical frequency from historical measurement data. Due to the limited data, the obtained transition probabilities are perturbed by errors. On the other hand, the performance of those approach without considering uncertainty could considerably be deteriorated by the transition probability errors. This motivates us to develop the robust MDP approach to mitigate the effect of the transition probability errors. In this section, we first formulate the problem as a robust MDP and propose a simple model to describe the transition probability uncertainty. We then develop robust MDP method to solve the problem.

Each robust optimization problem is defined by a three-tuple set, i.e., a nominal formulation, a definition of robustness and a uncertainty model. The nominal formulation of the robust MDP problem is defined by (3). The robustness of the policies is to mitigate the effect of transition probability uncertainty of the energy harvesting dynamic, i.e., to maximize the expected sum of the utilities based on the transition probabilities in the worst-case sense. The uncertainty set describes the range of possible transition matrix of the energy harvesting dynamic. Let Θ_n denote the uncertainty set of the transition matrix P_n in time slot n, where $P_n \in \Theta_n$. Let P denote the transition matrix sequence $\{P_1,\ldots,P_N\}$ and Θ denote the set of all possible sequences, where $P \in \Theta$. The robust problem is cast as follows:

$$\max_{a_1,\ldots,a_N} \min_{P\in\Theta} E\left\{\sum_{n=1}^{N} U\left(a_n, X_n\right)\right\} \tag{4}$$

where, the expectation is over the system state and the dynamic of the energy harvesting process is characterized by:

$$\{P_1,\ldots,P_N\}\in \Theta \tag{5}$$

For the uncertainty model, Θ_n is defined by $\Theta^0_n\times\Theta^1_n,\ldots,\Theta^{K-1}_n$, where Θ^i_n i = 0,…,K-1, is a subset of the probability simplicity in R^k. Let P^i_n denote the i-th row of the transition matrix P_n, we have $P^i_n \in \Theta^i_n$, where Θ^i_n of the i-th row is defined by:

$$\Theta^i_n=\{p|p_L \le p \le p_H,\ p^H1=1\} \tag{6}$$

where, p_L and p_H are the lower and the upper bound vectors, respectively. The uncertainty model (6) is a linear model, which characterizes the scope of possible transition probability vectors. The true transition vector lies in the uncertainty set given by (6). Next, we will derive the solution for the robust problem (4).

Lemma 1: For each initial system state X_1, the robust actions a^*_n can be obtained by implementing the following backward recursions from time slot N to 1:

$$\begin{cases} a^*_N = \arg\max_{a_N\in A}\left\{U\left(a_N, X_N\right)\right\} \\ J_N(X_N) = U(a^*_N, X_N) \end{cases} \tag{7}$$

and

$$\begin{cases} a^*_n = \arg\max_{a_n\in A}\min_{P^i_n\in\Theta^i_n} \\ \left\{U(a_n, X_n) + \sum_{X_{n+1}\in X} P(X_{n+1}|X_n,a_n)J_{n+1}(X_{n+1})\right\} \\ J_n(X_n) = \min_{P^i_n\in\Theta^i_n} \\ \left\{U\left(a^*_n, X_n\right) + \sum_{X_{n+1}\in X} P(X_{n+1}|X_n,a^*_n)J_{n+1}(X_{n+1})\right\} \\ n = 1,\ldots,N-1, \end{cases} \tag{8}$$

where P^i_n is the i-th row of the transition matrix P_n.

Proof: Please refer to the Theorem 1 in the reference (Nilim and Ghaoui, 2005).

Moreover, the robust policy can be obtained by the following algorithm.

Algorithm 1: The robust energy management approach
Input: the total number of time slot N, the action set A, the system state space X, the uncertainty set $\{P_1,\ldots,P_N\}$.
Output: the robust energy management policy:

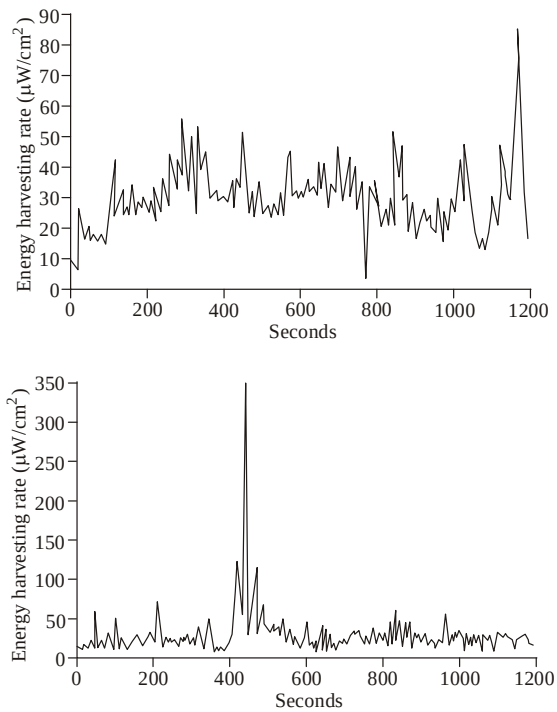

Fig. 2: Energy harvesting rate during 40 min

(1) n←N
(2) while (n≠0) do
for ($X_n \in X$) do
for ($a_n \in A$) do
if (n = N) do

$a^*_N = \arg\max_{a_N\in A}\{U(a_N, X_N)\}$,

$J_N(X_N) = U(a^*_N,X_N)$

else

$$a^*_n = \arg\max_{an\in A}\min_{P^i_n\in\Theta^i_n}$$

$$\left\{U(a_n, Xn) + \sum_{X_{n+1}\in X} P\left(X_{n+1}|X_n,a_n\right)J_{n+1}\left(X_{n+1}\right)\right\}$$

$$J_n(X_n) = \min_{P^i_n\in\Theta^i_n}\left\{U\left(a^*_n, X_n\right) + \sum_{X_{n+1}\in X} P\left(X_{n+1}|,a^*_n\right)J_{n+1}\left(X_{n+1}\right)\right\}$$

end
save $\{a^*_n, X_n\}$ into the robust policy table
end
end
(3) n = n-1
(4) end

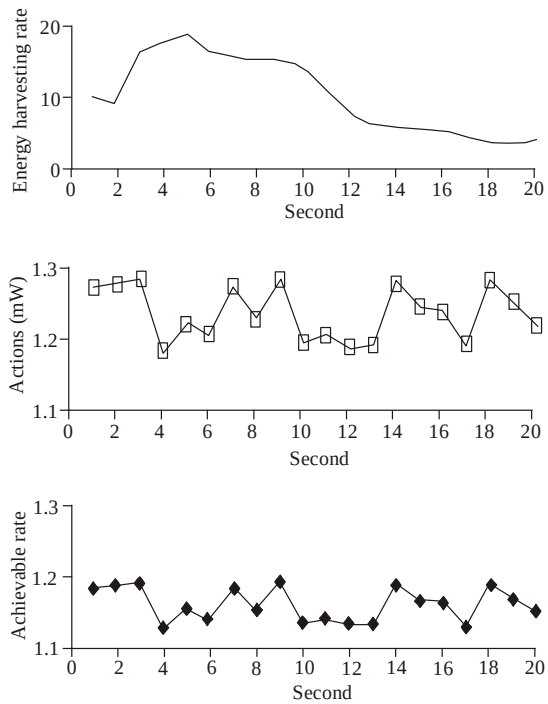

Fig. 3: Performances of the robust energy management approach (the initial battery level B_1 = 0.004J)

The robust policy can be computed in an off-line way and stored in a look-up table. We search the table according to the current system state and find out the corresponding optimal action when we implement this robust policy. In the next section, we will show the simulation results to verify our proposed schemes.

SIMULATION RESULTS

In the simulation studies, we use the energy harvesting data which is obtained by mobile energy harvesting sensors in New York city (EnHANTs Project, 2011). The energy harvesting traces in 40 min is shown is Fig. 2. We assume the area of the energy harvesting panel is set as 100 cm^2 and the length of each time slot is set as 1 s. It can be seen that the energy harvesting rate is time-varying and with large deviation. We use a Markov chain with 10 states to describe the energy harvesting process and the transition probability is estimated by counting the transition amount from the current state to the next state from these traces. The average SNR is set as 2 dB. We use 1000 realizations of energy traces during 10 s to compute the robust policy.

The performances of the robust energy management approach are shown in Fig. 3. It can be seen that the robust actions can efficiently track the variation of the energy harvesting rate. Compared to the energy harvesting rate, the actions have small deviation. It is due to the fact that the robust policy is not only based on current reward but also considers the sum of future rewards. The average achievable rate remains good under the uncertainty of the energy harvesting process.

CONCLUSION

In this study, we have proposed the robust energy management approach, which is to maximize the expected sum of the utility of the energy consumption rate under uncertainty of the energy harvesting process. In addition, we have proposed the framework of the robust control for the energy scheduling problem and the uncertainty model to describe the estimation errors of the energy harvesting process. The robust policy remains good performance under harvesting uncertainty. The simulation results have verified our theoretical claims.

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