

# Delay Limited Communication of Mobile Node with Wireless Energy Harvesting: Performance Analysis and Optimization

Dusit Niyato, *Member, IEEE*, and Ping Wang, *Member, IEEE*

**Abstract**—Wireless energy harvesting is a promising feature to provide energy supply to a wireless device. However, such wireless energy supply to a mobile node is random due to mobility. In this paper, we consider performance analysis and optimization for the mobile node with delay limited communication and wireless energy harvesting capability. Three major issues are considered, i.e., optimal transmission policy for the mobile node, energy management strategy and deployment of wireless power sources. Firstly, the constrained Markov decision process (CMDP) model is formulated and solved to obtain the optimal packet transmission policy to minimize the loss probability due to delay deadline violation. Secondly, the distributed energy management strategy of the wireless power source is analyzed. Specifically, the threshold-based strategy is considered, where the wireless power source releases wireless energy only when there are a certain number of mobile nodes in its harvesting coverage. Thirdly, the wireless power sources can be optimally deployed to minimize the long-term cost composed of deployment and power consumption costs. The analysis and optimization are presented in the unified framework which can be applied to the above issues jointly.

**Index Terms**—Delay sensitive, wireless energy harvesting, Markov chain

## I. INTRODUCTION

Wireless or radio frequency (RF) energy harvesting has emerged as a viable option to provide a power supply to mobile nodes [1]. One of the major issues when adopting wireless energy harvesting into wireless networks is the scheduling. The scheduling has to balance the tradeoff between energy harvesting and packet transmission due to limited resource (e.g., time and spectrum). This issue becomes much more complex for a mobile node whose wireless energy harvesting cannot be precisely planned. For the mobile node, the wireless energy can be harvested only when the node moves into the harvesting coverage of wireless power sources. Therefore, the wireless energy supply becomes random and unpredictable, and the energy and transmission scheduling of the mobile node has to take this fact into account. Beyond the mobile nodes, the operation and configuration of the wireless power sources are also important and can affect the performance of the mobile nodes significantly.

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In this paper, we consider wireless energy harvesting employed in a mobile node with delay limited communication as a random power supply. The mobile node can move among different locations. The node obliges to transmit delay constrained data periodically (e.g., a mobile sensor node). If the data cannot be transmitted before the delay deadline, the data will be discarded and considered to be lost. Given the strict delay deadline and random energy supply, the mobile node has to optimize its data transmission to meet quality of service (QoS) requirements. Apart from the data transmission of a mobile node, we also consider the issues related to wireless power sources. Firstly, to reduce power consumption, the wireless power sources can implement an energy management strategy to switch between active and inactive modes, where the wireless energy is and is not released to mobile nodes, respectively. Secondly, the wireless power sources can be deployed at the selected locations to minimize the long-term cost<sup>1</sup>, which is composed of deployment and power consumption costs. These issues have to be addressed taking the transmission performance of the mobile node into account.

To address above issues, we present the joint performance analysis and optimization framework for a mobile node with delay limited communication and wireless energy harvesting features. The framework considers the transmission optimization of the mobile node, the energy management strategy and deployment of wireless power sources jointly. The contributions of this paper are summarized as follows:

- We formulate an optimization problem to optimize the transmission policy for a mobile node. The objective is to minimize the packet loss probability due to violating a delay deadline given that the throughput of the mobile node is maintained at a target level. The optimization problem is based on a CMDP. Some extensions of the basic formulation (i.e., location specific performance requirements) are also given.
- We analyze the distributed energy management strategies of a wireless power source. We focus on the threshold-based strategy in which the wireless power source will be active when there are a certain number of nodes in its wireless energy harvesting coverage. The analysis to obtain power consumption performance of the wireless power source and the harvesting probability of the mobile node is presented.

<sup>1</sup>By the term “long-term”, we mean over the entire deployment duration of wireless power sources, which could be, for example, a couple of years.

- We consider the problem of wireless power source deployment. Given a set of candidate locations, wireless power sources can be deployed such that the total long-term cost can be minimized while the performance requirements of mobile nodes are met.

The rest of this paper is organized as follows. Section II presents a review of the related work. Section III describes the system model considered in this paper. Section IV introduces the queueing model for delay sensitive data transmission of a node with wireless energy harvesting. The optimal policy of data transmission is obtained by formulating and solving the Markov decision process (MDP) model. Section V presents the energy management strategy of the wireless power source given uncertainties of mobile nodes. Section VI presents the numerical performance evaluation results. Section VII concludes the paper.

## II. RELATED WORK

In this section, we provide a comprehensive review on three issues related to the energy harvesting, wireless energy transfer, and optimization of a wireless energy harvesting node. First, we introduce the works related to a general energy harvesting with wireless data transmission. These works discuss some fundamental issues and approaches. Specifically, the energy supply from energy harvesting is highly random. To achieve an optimal network performance, the stochastic optimization approach is the most suitable tool. Then, we review the works related to wireless data transmission and wireless energy transfer. While the wireless energy transfer provides more predictable energy supply, it might share the same spectrum with wireless data transmission. Thus, scheduling which balances the tradeoff between energy harvesting and packet transmission becomes an important issue. Finally, we discuss about the works related to the issues addressed in this paper. Specifically, stochastic optimization of the wireless nodes with energy harvesting. Also, we present an overview of energy management and deployment of base station.

### A. Energy Harvesting and Wireless Transmission

Energy harvesting for wireless nodes is an important issue [2]. With energy storage (i.e., battery), the wireless nodes can harvest and store energy from an environment, perpetuating their operations. However, energy harvesting is highly random by nature. The energy supply is sporadic and unpredictable (e.g., solar, wind, and RF). In [2], a comprehensive survey of sensor nodes with an energy harvesting capability was provided. It highlighted that not only radio resource is needed for data transmission, but also energy must be optimized to achieve an objective of a network. Many analyses and optimizations of wireless nodes with energy harvesting based on Markov chain were presented in the literature. For example, in [3], an energy management mechanism was introduced to switch the node between active and sleep modes given randomness of energy supply (i.e., solar power). An analysis based on Markov chain was presented, which can be used to optimize the performance of the sensor/mesh node. The authors in [4] studied and optimized the performance of a

sensor network with cooperative communications and energy harvesting. The scheduling strategy for the network was presented, in which its optimal solution is obtained from the MDP and partially observable MDP (POMDP) models for complete and incomplete network state information, respectively. The scheduling can be integrated with a medium access control (MAC) protocol used by the node with energy harvesting. In [5], the analysis and design of different MAC protocols (i.e., TDMA, framed-ALOHA (FA), and dynamic-FA (DFA)) was presented. The Markov chain model was developed to analyze the delivery probability (i.e., capability of the MAC protocol to successfully deliver a packet to a destination).

### B. Wireless Energy Transfer and Harvesting

With advanced electronic design, wireless energy transfer, which is one form energy harvesting, is being adopted for wireless nodes, e.g., sensor networks [12], [13], [14]. [15] presented the prototype implementation of wireless energy harvesting sensor networks. The networks harvest energy from TV broadcast airwaves (VHF and UHF for analog and digital TV, respectively). It was shown that over 7 days a week, the energy around 20 micro-watts can be harvested regularly in most of the daytime. The similar prototype and study were done for 2.4 GHz ISM band [16], where the average powers of 0.052 and 0.011 micro-watts can be harvested from Wi-Fi access point at the distances of 2 and 10 meters, respectively. The interested reader can refer to above references for the technical detail of RF or wireless energy harvesting.

One of the main applications of wireless energy transfer is in sensor networks. A few works started exploring this technology. In [22], a “Qi-Ferry” device was introduced. The Qi-Ferry is charged and moves from an energy station to visit sensor nodes to wirelessly supply energy, extending sensors’ lifetime. The authors in [23] considered a similar device where a mobile charging unit periodically moves and charges sensor nodes wirelessly. They proposed an optimization model with the objective to maximize the ratio of vacant time of the mobile charging unit over the cycle time. The optimal traveling path for the unit is obtained.

A transmission strategy and protocol design are also as of importance for the wireless energy harvesting node. The reason is due to the fact that the wireless energy will be harvested using the same interface for data transmission. Therefore, traffic and energy harvest scheduling problem arises. Some solutions exist in the literature. For example, the authors in [17] introduced an optimal mode switching between energy harvesting and information decoding based on instantaneous channel and interference condition. The minimum transmission outage probability and maximum capacity were derived for delay-limited and no-delay-limited communication, respectively. The similar problem was studied for the MIMO broadcast channel in [18] and beamforming in [19]. In [20], the transmission throughput of the wireless energy harvesting node was optimized. The optimization problem was formulated for the power allocation and slot selection policy. The objective is to maximize network capacity given the constraint on power consumption (i.e., transmission and

circuit power consumption). The problem was shown to be convex and the modified water-filling algorithm was applied. Alternatively, from a protocol design perspective, the energy adaptive MAC protocol (EA-MAC) was proposed in [21]. The protocol aims to adapt a duty cycle of the sensor node according to the amount of energy harvested and transmission contention duration needed to achieve fairness data transfer among multiple nodes. The analytical model based on Markov chain was also introduced.

Clearly, resource management issue becomes crucial in wireless energy transfer and harvesting due the sharing of spectrum. The mathematical tools, which are able to model randomness of energy supply and other system parameters, will be needed.

### C. Stochastic Optimization of Energy Harvesting Node

Markov chain and MDP were also adopted to analyze and optimize the performance of the wireless energy harvesting node. In [24], the RFID scheduling which considers tradeoff between energy harvesting rate and successful transmission probability was optimized using MDP. The objective is to maximize read probability of an RFID tag. The Howard policy improvement algorithm was applied to obtain an optimal transmission policy. In [25], POMDP was used to obtain an optimal mode selection of the sensor node with wireless energy harvesting. The node opportunistically harvests wireless energy from primary networks, and hence the node cannot transmit data at the same time. The optimal mode selection instructs the node to decide whether to harvest energy or to transmit data. In [26], the wireless energy harvesting in a cooperative network was considered. The relay node not only forwards received data, but also harvests energy from the source. A greedy policy was introduced for the relay to transmit given the energy state. The system was modeled as a Markov chain, which can be used to derive the outage probability. In addition, a genie-aided policy, assuming complete transmission and energy information, was used to determine the lower bound performance for the comparison purpose.

Some works studied delay performance of wireless transmission. In [6], the delay constraint with wireless energy harvesting was considered. However, the model accounts for only the average delay metrics. The queueing model based on M/G/1 was used, which could not capture the correlation between energy and delay states. In [7], the MDP model was formulated to determine an optimal transmission policy of the delay-limited communication. The node decides based on available energy in its storage to transmit or drop an arriving packet. The learning algorithm was also introduced to obtain the policy.

Another related issue is the energy management and deployment of base stations or relay stations, which is a fundamental problem in green communications [8]. The authors in [9] investigated the tradeoff between the number of deployed relay stations and base station in terms of energy consumption. The adaptive resource allocation scheme for base stations and relay stations was proposed to reduce energy consumption. In [10], the total base station energy consumption per area

under different deployment strategy was studied. Given the requirement of the receive power at the cell edge, it is found that if a fixed power consumption overhead exists, it is not optimal to deploy too dense base stations. However, there is an optimal cell size which could achieve the minimum energy consumption. Such optimal cell size can be analyzed using the theoretical model proposed in [10]. In [11], an impact of deploying micro base stations in additional to macro cell with an objective to reduce power consumption of the network was studied. The area power consumption is defined as a metric to be optimized.

We can summarize the differences between existing work and this paper as follows.

- Existing stochastic optimization models developed for wireless energy transfer did not consider delay limited communication. Many of them study the system capacity, without actual traffic generation process.
- Existing optimization models for delay limited communication did not take the wireless energy transfer into account. Some models were proposed for general energy harvesting, but not take the unique characteristic of wireless energy transfer into consideration, thus could not be applied directly to wireless energy transfer. Specifically, the wireless energy transfer is more predictable and controllable than other forms of energy harvesting. Controllability introduces the new dimension of the optimization.
- Existing works related to energy management and deployment of base stations did not consider wireless energy transfer.

## III. SYSTEM MODEL

### A. Mobile Node

We consider a mobile node with wireless data transmission and wireless energy harvesting capabilities. For the wireless transmission, the data to be transmitted is delay limited. In particular, after the data (i.e., packet) is generated (e.g., from a sensor device), the packet has to be transmitted within the delay deadline. If the packet cannot be transmitted successfully within the delay deadline, the packet will be discarded. The new packet will be generated after the earlier packet has been successfully transmitted or discarded due to violating the delay deadline. If the packet is unsuccessfully transmitted (e.g., due to channel error), the packet will be retransmitted until it is successfully transmitted (i.e., based on an ARQ mechanism) or the delay deadline is reached. The packet can be transmitted only if the mobile node has enough energy in a storage (e.g., battery). The capacity of the energy storage is finite with  $E$  units. The energy storage is replenished from a wireless energy harvesting interface. We assume that the wireless energy harvesting generates one unit of energy per time slot if the node is in the harvesting coverage of an active wireless power source and one unit of energy is sufficient for transmitting one packet. We consider a typical scenario of broadcast wireless energy transfer. In this scenario, if the mobile nodes are in the harvesting coverage of the power source, all of them will be able to harvest wireless energy [27], [28]. The energy harvesting by the mobile node is successful with

the probability  $c_l$  at location  $l$ . This probability can be different for different mobile node, for example, depending on channel fading. The wireless power source is active when it releases wireless energy in a time slot.

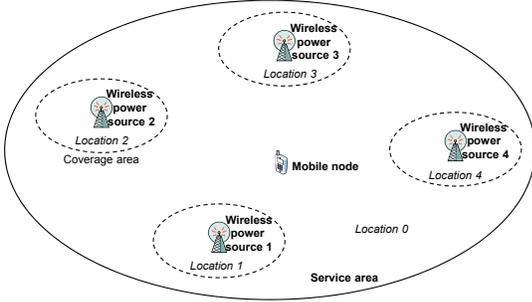


Fig. 1: Service area of delay limited packet transmission with wireless energy harvesting.

### B. Service Area and Node's Mobility

The mobile node can move in a service area (e.g., target sensing area). The service area is composed of  $L+1$  locations, and the set of locations is denoted by  $\mathcal{L} = \{0, 1, \dots, L\}$ .  $l = 0$  corresponds to the location that the node is not in the harvesting coverage of any power sources.  $l \in \{1, \dots, L\}$  corresponds to the location of the harvesting coverage of power source  $l$ . In other words, we consider the discrete mobility model of the mobile node (i.e., movement of the mobile node is based on a set of finite discrete locations). An example of the service area is shown in Fig. 1. There are four power sources and hence the set of locations is  $\mathcal{L} = \{0, 1, \dots, 4\}$ . The node's mobility is modeled by the transition matrix  $\mathbf{M}$  defined as follows:

$$\mathbf{M} = \begin{bmatrix} M_{0,0} & \cdots & M_{0,L} \\ \vdots & \ddots & \vdots \\ M_{L,0} & \cdots & M_{L,L} \end{bmatrix} \quad (1)$$

where  $M_{l,l'}$  for  $l, l' \in \mathcal{L}$  is the probability that the mobile node is at location  $l$  in the current time slot and moves to location  $l'$  in the next time slot.

We assume that the probability of successful packet transmission is location dependent. The probability of successful packet transmission by a mobile node in a time slot is denoted by  $\kappa_l$ . In this case, if the mobile node uses the same interface for data transmission and energy harvesting, the data transmission cannot be performed when the mobile node is in the harvesting coverage of an active wireless power source (i.e.,  $\kappa_0 > 0$  and  $\kappa_l = 0$  for  $l \in \{1, \dots, L\}$ ). On the other hand, if the node uses different interfaces for data transmission and energy harvesting and the wireless energy does not overlap with the transmission spectrum, then  $\kappa_l > 0$  for  $l \in \mathcal{L}$ . The following analysis and optimization are formulated for the latter case. However, the extension for the former case is also straightforward (i.e., through defining the probability of successful packet transmission accordingly).

### C. Performance Analysis and Optimization Framework

A mobile node has an objective to minimize the packet loss. In this case, the packet will be lost only when the delay deadline has been passed but it has not been successfully transmitted. The delay deadline is denoted by  $D$  time slots. To transmit a packet, the mobile node needs to have sufficient energy in its storage. Since the node can move in a service area, the node can harvest wireless energy sporadically, i.e., when it moves into harvesting coverage of a wireless power source. Therefore, the mobile node has to make a decision when to transmit a packet given the delay state (i.e., the delay that a current packet has already experienced) and energy state (i.e., the available energy in the storage). To obtain an optimal transmission policy for the mobile node, Section IV introduces the optimization based on a CMDP. The policy aims to minimize loss probability while maintaining throughput of the mobile node at the target level.

Then, an energy management strategy of wireless power sources is considered. The wireless power sources may consume too much electricity if they continuously release wireless energy. Therefore, we propose that the wireless power sources can switch between active and inactive modes to release and do not release wireless energy, respectively. One of the strategies is based on the number of mobile nodes in their harvesting coverage. The analysis and optimization of the wireless power sources are proposed in Section V. In addition, the deployment of power sources is also considered such that the packet loss requirement of the mobile node must be met.

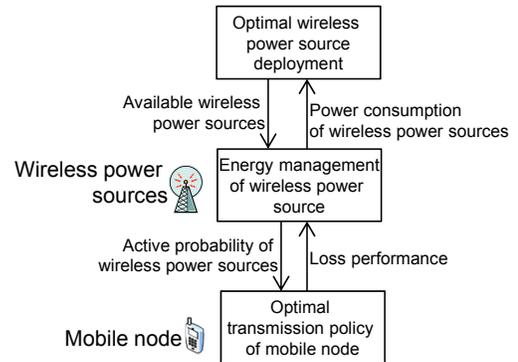


Fig. 2: Optimal transmission policy of a mobile node, energy management strategy and deployment of wireless power sources.

Fig. 2 shows the structure of the proposed performance analysis and optimization framework. The relationship among the optimal transmission policy of a mobile node, energy management and deployment of wireless power sources is shown. Specifically, solving for an optimal transmission policy requires the energy harvesting probability of the mobile node. This probability can be derived from the probability that the wireless power source is active. The probabilities that wireless power sources are active are influenced by the energy management strategy used. The energy management uses the mobile node performance (i.e., loss probability) together with the set of deployed wireless power sources to determine the best strategy. Based on the energy management strategy of

wireless power sources, their suitable deployment will be determined.

#### IV. OPTIMAL TRANSMISSION POLICY OF MOBILE NODE

In this section, the optimization model based on a CMDP is formulated and solved to obtain an optimal transmission policy for a mobile node with wireless energy harvesting. First, the state and action spaces of the CMDP model are defined. Then the transition matrix is derived and the optimal policy is obtained. The performance measures are also presented.

##### A. State Space and Action Space

The state space of the mobile node is defined as follows:

$$\Theta = \{(\mathcal{D}, \mathcal{E}, \mathcal{L}); \mathcal{D} \in \{0, 1, \dots, D\}, \mathcal{E} \in \{0, 1, \dots, E\}, \mathcal{L} \in \mathcal{L}\} \quad (2)$$

where  $\mathcal{D}$ ,  $\mathcal{E}$ , and  $\mathcal{L}$  are the delay, energy, and location states, respectively.  $D$  and  $E$  are the delay deadline and energy storage capacity, respectively. The state is then defined as a composite variable  $\theta = (d, e, l) \in \Theta$ , where  $d$ ,  $e$ , and  $l$  are the delay, level of available energy, and location, respectively.

The action space is defined as follows:

$$\Delta(\theta) = \begin{cases} \{0\}, & \text{if } e = 0 \\ \{0, 1\}, & \text{otherwise} \end{cases} \quad (3)$$

where 1 and 0 correspond to actions “transmit” and “do not transmit” (i.e., “wait”), respectively. In this case, the mobile node can transmit the packet if there is energy in its storage.

##### B. Transition Probability Matrix

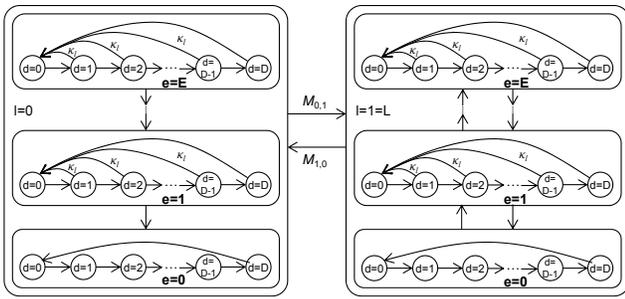


Fig. 3: State transition diagram.

Fig. 3 shows an example of a state transition diagram for an action “transmit” when there are two locations,  $l = 0, 1$ . At location  $l = 0$ , the energy level cannot increase, since the mobile node is not in the harvesting coverage of any wireless power source. Therefore, there are only downward arrow lines. In contrast, at location  $l = 1$ , the energy level can increase, since the mobile node is in the harvesting coverage of one of the wireless power sources. Therefore, there are both downward and upward arrow lines. In both cases, when the energy level is  $e = 0$ , the mobile node cannot successfully transmit a packet due to lack of energy. The state transition probability matrix can be derived accordingly.

1) Action “transmit”: The probability matrix  $\mathbf{E}(\delta)$  for the energy state transition under the action “transmit” (i.e.,  $\delta = 1$ ) is defined as follows:

$$\mathbf{E}(1) = \begin{bmatrix} \mathbf{A}_{0,0} & \mathbf{A}_{0,1} & & & & \\ \mathbf{A}_{1,0} & \mathbf{A}_{1,1} & & & & \\ & \mathbf{A}_{2,1} & \mathbf{A}_{2,2} & & & \\ & & & \ddots & & \\ & & & & \mathbf{A}_{E,E-1} & \mathbf{A}_{E,E} \end{bmatrix} \quad (4)$$

where  $\mathbf{A}_{e,e'}$  is the probability matrix for location transitions. In (4), the energy level can decrease or remain the same when the action is to transmit. However, the exception is at when the energy level is zero, in which the action “transmit” cannot be taken. Therefore, if there is the harvested wireless energy, the energy level can increase. The probability matrix  $\mathbf{A}_{e,e'}$  is defined as follows:

$$\mathbf{A}_{0,0} = \mathbf{M}(\mathbf{I} - \mathbf{C}), \quad \mathbf{A}_{0,1} = \mathbf{M}\mathbf{C} \quad (5)$$

$$\mathbf{A}_{e,e-1} = \mathbf{M}(\mathbf{I} - \mathbf{C}), \quad \mathbf{A}_{e,e} = \mathbf{M}\mathbf{C} \text{ for } e = \{1, \dots, E\} \text{ and} \quad (6)$$

$$\mathbf{C} = \begin{bmatrix} 0 & & & & \\ & c_1 & & & \\ & & \ddots & & \\ & & & c_L & \end{bmatrix}, \quad (7)$$

where  $c_l$  is the probability that a mobile node harvests one unit of energy in a time slot from the wireless power source  $l$ , for  $l \in \{1, \dots, L\}$ . This probability, referred to as the harvesting probability, depends on the energy management strategy of the wireless power source. The analysis of this probability will be discussed in Section V.  $\mathbf{I}$  is an identity matrix with an appropriate size.

The probability matrix  $\mathbf{P}(\delta)$  for the delay state transition for the action “transmit” (i.e.,  $\delta = 1$ ) is defined as follows:

$$\mathbf{P}(1) = \begin{bmatrix} \mathbf{D}_{0,0}(1) & \mathbf{D}_{0,1}(1) & & & \\ \mathbf{D}_{1,0}(1) & & \mathbf{D}_{1,2}(1) & & \\ \vdots & & & \ddots & \\ \mathbf{D}_{D-1,0}(1) & & & & \mathbf{D}_{D-1,D}(1) \\ \mathbf{D}_{D,0}(1) & & & & \mathbf{0} \end{bmatrix} \quad (8)$$

where  $\mathbf{D}_{d,d'}(1)$  is the probability matrix for location and energy state transitions, when the action is “transmit” (i.e.,  $\delta = 1$ ). In (8), the delay of a packet can increase or reset to zero if the mobile node unsuccessfully and successfully transmits the packet, respectively. The probability matrix  $\mathbf{D}_{d,d'}(1)$  for when the delay is  $d$  in the current time slot and becomes  $d'$  in the next time slot is defined as follows:

$$\mathbf{D}_{d,d+1}(1) = \mathbf{E}(1)(\mathbf{I} - \mathbf{S}), \quad \mathbf{D}_{d,0}(1) = \mathbf{E}(1)\mathbf{S}, \quad \mathbf{D}_{D,0}(1) = \mathbf{E}(1) \quad (9)$$

where  $\mathbf{S}$  is the diagonal matrix whose diagonal element is defined as follows:

$$S_{e(L+1)+l+1, e(L+1)+l+1} = \begin{cases} \kappa_l, & e > 0 \\ 0, & e = 0 \end{cases} \quad (10)$$

for  $e = 0, 1, \dots, E$  and  $l = 0, 1, \dots, L$ , where  $S_{k,k}$  is the element at row and column  $k$  of the matrix  $\mathbf{S}$ . The element  $S_{e(L+1)+l+1, e(L+1)+l+1}$  corresponds to the successful packet transmission when the mobile node is at location  $l$  and its energy level is  $e$ . The value of this element is zero if the energy level is zero. Note that the size of matrix  $\mathbf{S}$  is the same as that of  $\mathbf{E}(\delta)$ .



offline (e.g., on a server) and the optimal policy can be downloaded to the mobile node.

The transmission policy, which is the probability of taking a particular action at a certain state, can be obtained from the solution  $\phi^*(\theta, \delta)$  of the above LP model. The transmission policy for the mobile node with wireless energy harvesting is obtained from

$$\pi^*(\theta, \delta) = \frac{\phi^*(\theta, \delta)}{\sum_{\delta' \in \Delta} \phi^*(\theta, \delta')}, \text{ for } \theta \in \Theta \text{ and } \sum_{\delta' \in \Delta} \phi^*(\theta, \delta') > 0. \quad (26)$$

If  $\sum_{\delta' \in \Delta} \phi^*(\theta, \delta') = 0$ , then the specific action “wait” is taken.

The CMDP and LP models presented in (19)-(20) and (21)-(25), respectively, are given for a basic case. Two possible extensions of the formulation (i.e., to include a location specific throughput constraint and to balance performance at different location) are given in the Appendix.

#### D. Performance Measures

Given any policy  $\pi(\theta, \delta)$  (e.g., an optimal policy obtained from (26)), the performance measures of the mobile node with wireless energy harvesting can be analyzed. Let  $\mathbf{p}_k(\delta)$  denote the row matrix at row  $k$  of the matrix  $\mathbf{P}(\delta)$ , where

$$\mathbf{P}(\delta) = \begin{bmatrix} \mathbf{p}_1(\delta) \\ \vdots \\ \mathbf{p}_{(D+1)(E+1)(L+1)}(\delta) \end{bmatrix}. \quad (27)$$

$(D+1)(E+1)(L+1)$  is the size of matrix  $\mathbf{P}(\delta)$ . The transition matrix when the policy  $\pi(\theta, \delta)$  is applied can be expressed as follows:

$$\mathbf{P}_\pi = \begin{bmatrix} \pi((0, 0, 0), 1)\mathbf{p}_1(1) \\ \vdots \\ \pi((D, E, L), 1)\mathbf{p}_{(D+1)(E+1)(L+1)}(1) \\ \pi((0, 0, 0), 0)\mathbf{p}_1(0) \\ \vdots \\ \pi((D, E, L), 0)\mathbf{p}_{(D+1)(E+1)(L+1)}(0) \end{bmatrix} \quad (28)$$

Then, the stationary probability of the mobile node can be obtained by solving the following equations  $\vec{\eta}^T \mathbf{P}_\pi = \vec{\eta}^T$  and  $\vec{\eta}^T \mathbf{1} = 1$ , where  $\mathbf{1}$  is a vector (with an appropriate size) of ones.  $\vec{\eta}$  whose element is  $\eta(d, e, l)$  is the stationary probability vector of the mobile node, i.e.,

$$\vec{\eta}^T = [ \eta(0, 0, 0) \quad \cdots \quad \eta(d, e, l) \quad \cdots \quad \eta(D, E, L) ]. \quad (29)$$

Given this stationary probability, the following performance measures of the mobile node can be obtained.

1) *Delay Distribution and Average Delay*: The delay distribution of the successfully transmitted packet can be obtained from

$$\beta(d) = \sum_{e=1}^E \sum_{l=0}^L \eta(d, e, l) \pi((d, e, l), 1) \kappa_l. \quad (30)$$

The delay distribution corresponds to the probability of successful transmission when the action is “transmit” (i.e.,  $\delta = 1$ )

and the energy level is greater than zero. The average delay can be obtained from

$$\bar{d} = \sum_{d=0}^D d \beta(d). \quad (31)$$

2) *Throughput*: The throughput of the mobile node is obtained as follows:

$$v = \sum_{e=1}^E \sum_{l=0}^L \sum_{d=0}^D \eta(d, e, l) \pi((d, e, l), 1) \kappa_l. \quad (32)$$

This throughput is the number of successfully transmitted packets per time slot. Note that this throughput is similar to the “on-time throughput” metric [30].

3) *Loss Probability*: The loss probability is obtained from

$$\lambda = \sum_{l=0}^L \sum_{\delta=0}^1 \eta(D, 0, l) \pi((D, 0, l), \delta) + \sum_{e=1}^E \sum_{l=0}^L \eta(D, e, l) \left( \pi((D, e, l), 1) (1 - \kappa_l) + \pi((D, e, l), 0) \right). \quad (33)$$

The first term is the loss when there is no sufficient energy in the storage. The second and third terms are the losses due to unsuccessful transmission and “wait” action, respectively. All the losses happen when the delay deadline  $D$  is reached. Note that the loss probability obtained in (33) is referred to as the “absolute loss” which is the probability that at any point in time, the packet is observed to be lost. The loss ratio (i.e., proportion of the generated packets which result in loss) is obtained as follows:

$$\lambda_{\text{rat}} = \frac{\lambda}{\lambda + v} \quad (34)$$

where  $v$  is the throughput (i.e., successful transmission). Similarly, the success ratio (i.e., proportion of the generated packets which result in successful transmission) is obtained from

$$v_{\text{rat}} = \frac{v}{\lambda + v}. \quad (35)$$

4) *Average Energy Level*: The average energy level in the storage of the mobile node is obtained from

$$\bar{e} = \sum_{d=0}^D \sum_{e=0}^E \sum_{l=0}^L \sum_{\delta=0}^1 e \eta(d, e, l) \pi((d, e, l), \delta). \quad (36)$$

In the next section, based on the transmission policy of the mobile node, the energy management strategy and deployment of wireless power sources will be presented.

## V. ENERGY MANAGEMENT AND WIRELESS POWER SOURCE DEPLOYMENT

In this section, we discuss some energy management strategies of wireless power sources. The performance analysis for different strategies is presented and will be used to optimize a transmission policy of the mobile node. In particular, the energy management strategy determines the harvesting probability  $c_l$  of the mobile node which is used in (7). Then, the power source deployment issue is considered afterward.

### A. Power Source Energy Management Strategies

We assume that the wireless power source is active and inactive when it releases and does not release wireless energy, respectively. We consider three energy management strategies to control an active/inactive mode of the wireless power source.

- *Always Active:* This is the most primitive strategy. A wireless power source always releases wireless energy. The mobile nodes will always be able to harvest wireless energy when they are in the harvesting coverage of the wireless power source. In this case, the harvesting probability of the mobile node from wireless power source  $l$  is  $c_l = 1$ .
- *Probabilistic:* In this strategy, a wireless power source releases wireless energy with some probability. The mobile nodes can probabilistically harvest wireless energy when they are in the harvesting coverage of the wireless power source. Let  $\sigma_l$  denote the probability of releasing wireless energy by wireless power source  $l$ . The harvesting probability of the mobile node is  $c_l = \sigma_l$ .
- *Threshold-Based:* Assume that the wireless power source can detect the mobile nodes which are in its harvesting coverage. Therefore, the wireless power source can release wireless energy when the number of mobile nodes in the harvesting coverage is equal to or larger than the threshold  $\omega_l$ . This threshold is basically the minimum required number of mobile nodes to activate the wireless power source.

Note that the above energy management strategies are fully distributed. In particular, they use only local information to activate the wireless power source. The centralized strategy which uses global information (e.g., when multiple wireless power sources coordinate their wireless energy distribution) is an interesting research issue and open as the future work.

Although the “always active” and “probabilistic” strategies are simple to implement, they suffer from energy wastage, if the wireless energy is released without or with small number of mobile nodes in the harvesting coverage. Alternatively, the threshold-based strategy can efficiently release wireless energy only when some certain number of mobile nodes are in the harvesting coverage and are able to harvest energy from the wireless power source. Note that the wireless power source can detect the mobile nodes in its harvesting coverage by different techniques. One of them is similar to that for an RFID, where the wireless power source releases wireless energy for a short period of time (i.e., energy pulse). The mobile node can use that energy to reply its identity back to the wireless power source.

In the following, we present an analysis for the harvesting probability of the mobile node given a threshold  $\omega_l$  for  $l = 1, \dots, L$ . Let  $\vec{\mu}$  denote the stationary probability vector for the mobility of a mobile node. An element of this matrix is denoted by  $\mu_l$  which is the probability that the mobile node is at location  $l$ . The vector can be obtained by solving  $\vec{\mu}^T \mathbf{M} = \vec{\mu}^T$  and  $\vec{\mu}^T \mathbf{1} = 1$ , where  $\mathbf{M}$  is the mobility transition matrix as defined in (1). Let  $N$  denote the total number of mobile nodes in the service area. The probability that there are  $n_l$

mobile nodes at location  $l$  is obtained from

$$\phi(n_0, \dots, n_L, N, \mu_0, \dots, \mu_L) = \begin{cases} \frac{N!}{n_0! \dots n_L!} (\mu_0)^{n_0} \dots (\mu_L)^{n_L}, & \sum_{l=0}^L n_l = N \\ 0, & \text{otherwise} \end{cases} \quad (37)$$

which is a multinomial distribution.

First, we obtain the probability that the tagged node and at least other  $\omega_l - 1$  nodes are at location  $l$  so that the total number of nodes in the harvesting coverage of the wireless power source  $l$  is  $\omega_l$  as in (38) where  $n_l \geq 0$  for  $l \neq l'$ . Then, the harvesting probability is obtained from

$$c_l = \frac{\hat{\gamma}_l(\omega_l)}{\mu_l} \quad (39)$$

for the threshold-based energy management strategy.

The probability that the wireless power source  $l$  will be active and release wireless energy can be obtained from (40). If the wireless power source  $l$  consumes  $w_l$  unit of power when it is active, then the average power consumption is

$$\bar{W}_l = w_l A_l. \quad (41)$$

It is straightforward to see that the harvesting probability of the mobile node is a non-increasing function of a threshold  $\omega_l$ . In particular, increasing threshold  $\omega_l$  entails more mobile nodes to be in the corresponding location to activate the wireless power sources. Therefore, the probability that the mobile node will be able to harvest energy from wireless power source  $l$  decreases or remains the same. Given the transmission policy  $\pi(\theta, \delta)$ , the feasible region for the thresholds of all wireless power sources such that the loss probability of the mobile nodes can be maintained below the loss requirement  $R$  can be established as follows:

$$\Omega(R) = \left\{ \boldsymbol{\omega} = (\omega_1, \dots, \omega_L); \lambda(\omega_1, \dots, \omega_L) \leq R \right\} \quad (42)$$

where  $\lambda(\cdot)$  is the loss probability obtained from (33). In this case, the loss probability is defined as a function of thresholds of all wireless power sources. In practice, to determine the feasible region, only the loss probability of the mobile node needs to be transferred to the power sources. As a result, the corresponding overhead is significant. Then, the feasible region can be obtained from Algorithm 1. The idea behind the Algorithm 1 is that if an infeasible threshold is detected, due to the non-increasing harvesting probability property, the algorithm will skip checking for any threshold larger than the infeasible threshold at the same wireless power source.

From a feasible region  $\Omega(R)$ , the thresholds which minimize the total power consumption of all wireless power sources can be determined as follows:

$$\min_{\boldsymbol{\omega}} \sum_{l=1}^L W_l(\boldsymbol{\omega}), \quad \text{where } W_l(\boldsymbol{\omega}) = w_l A_l(\boldsymbol{\omega}) \quad (43)$$

$$\text{s.t. } W_l(\boldsymbol{\omega}) < W_{l,\max} \quad (44)$$

$$\boldsymbol{\omega} \in \Omega(R) \quad (45)$$

where  $A_l(\boldsymbol{\omega})$  and  $W_l(\boldsymbol{\omega})$  are the probability of wireless power source  $l$  to be active and the power consumption of

$$\hat{\gamma}_l(\omega_l) = \sum_{n'_l=\omega_l-1}^{N-1} \left( \sum_{\substack{(n_0, \dots, n_{l-1}, n_{l+1}, \dots, n_L) \\ n_0 + \dots + n'_l + \dots + n_L = N-1}} \mu_l \phi(n_0, \dots, n'_l, \dots, n_L, N-1, \mu_0, \dots, \mu_L) \right) \quad (38)$$

$$A_l = \sum_{n'_l=\omega_l}^N \left( \sum_{\substack{(n_0, \dots, n_{l-1}, n_{l+1}, \dots, n_L) \\ n_0 + \dots + n'_l + \dots + n_L = N}} \phi(n_0, \dots, n'_l, \dots, n_L, N, \mu_0, \dots, \mu_L) \right). \quad (40)$$

**Algorithm 1** Algorithm to obtain the feasible region of thresholds (i.e., the minimum required number of mobile nodes to activate wireless power sources) in threshold-based energy management strategy.

---

```

1: Sort wireless power sources such that  $\mu_l \geq \mu_{l+1}$  and initialize  $\Omega \leftarrow \emptyset$ 
2: while  $\omega_1 \leq N$  do
3:    $\omega_2 \leftarrow 1, f_2 \leftarrow 1$ 
4:   while  $\omega_2 \leq N$  and  $f_2 = 1$  do
5:      $\omega_3 \leftarrow 1, f_3 \leftarrow 1$ 
6:      $\vdots$ 
7:     while  $\omega_{L-1} \leq N$  and  $f_{L-1} = 1$  do
8:        $\omega_L \leftarrow 1, f_L \leftarrow 1$ 
9:       while  $\omega_L \leq N$  and  $f_L = 1$  do
10:        if  $\sum_{l=1}^L \omega_l = N$  then
11:          if  $\lambda(\omega_1, \dots, \omega_L) \leq R$  then
12:             $\Omega \leftarrow \Omega \cup \{(\omega_1, \dots, \omega_l, \dots, \omega_L)\}$  {Add feasible thresholds}
13:          else
14:             $f_L \leftarrow 0$  {Infeasible thresholds}
15:          end if
16:           $\omega_L \leftarrow \omega_L + 1$ 
17:        end if
18:      end while
19:      if  $f_L = 0$  and  $\omega_L = 2$  then
20:         $f_{L-1} \leftarrow 0$  {Skip the current value of  $\omega_{L-1}$  since it is infeasible}
21:      end if
22:       $\omega_{L-1} \leftarrow \omega_{L-1} + 1$ 
23:     $\vdots$ 
24:     $\omega_3 \leftarrow \omega_3 + 1$ 
25:  end while
26:  if  $f_L = 0$  and  $\omega_3 = 2$  then
27:     $f_2 \leftarrow 0$  {Skip the current value of  $\omega_2$  since it is infeasible}
28:  end if
29:   $\omega_2 \leftarrow \omega_2 + 1$ 
30: end while

```

---

wireless power source  $l$  (i.e., from (40) and (41), respectively), defined as the functions of thresholds  $\omega$ . The constraint in (44) imposes the maximum power consumption  $W_{l,\max}$  of each wireless power source at location  $l$ . The solution  $\omega$  of (43)-(45) can be obtained by simply modifying Algorithm 1. Specifically, at Line 11, the thresholds which yield the minimum total power consumption of all wireless power sources can be identified.

Note also that the threshold-based power source energy management strategy could depend on the mobile node density in the service area. Nevertheless, determining the feasible region will ensure that all of the mobile nodes will meet the

transmission performance requirement.

### B. Wireless Power Source Deployment

In addition to implementing an energy management strategy for wireless power sources to reduce power consumption cost with the QoS requirement of mobile nodes, wireless power sources can be selectively deployed to minimize long-term cost. Let  $\hat{\mathcal{L}}$  denote a set of candidate locations and  $W_l(\omega, \mathcal{L}_D)$  denote the power consumption of wireless power source  $l$  if this power source is deployed (i.e.,  $l \in \mathcal{L}_D$ ). The power consumption is defined as a function of  $\mathcal{L}_D$ , i.e., a set of deployed wireless power sources, where  $\mathcal{L}_D \subseteq \hat{\mathcal{L}}$ . The optimization problem for the wireless power source deployment can be formulated as follows:

$$\min_{\mathcal{L}_D} \sum_{l \in \mathcal{L}_D} \left( W_l^\dagger(\omega, \mathcal{L}_D) + X_l \right) \quad (46)$$

$$\text{s.t.} \quad \mathcal{L}_D \subseteq \hat{\mathcal{L}} \quad (47)$$

where  $X_l$  is the deployment cost of a wireless power source  $l \in \mathcal{L}_D$ . Here  $W_l^\dagger(\omega, \mathcal{L}_D)$  is the minimum power consumption of the wireless power source  $l$  such that the loss requirement is met (i.e., the solution of (43)-(45)). The solution of (46)-(47) can be obtained by enumeration due to combinatorial nature of the problem. Specifically, a decision of deploying one wireless power source will affect the power consumption of the rest of wireless power sources. An efficient algorithm to obtain the solution is an open issue and can be addressed in the future work.

Algorithm 2 summarizes the steps for transmission optimization of the mobile node, energy management and deployment of wireless power sources.

## VI. PERFORMANCE EVALUATION

### A. Parameter Setting

We consider a service area with four wireless power sources 1, ..., 4 at locations 1, ..., 4, respectively. Location 0 does not have a wireless power source. Unless stated otherwise, the following parameter setting is used for the performance evaluation. The energy storage capacity of a mobile node is 10 units. The energy consumption parameters are assumed to be similar used in [23]. The delay deadline is 10 time slots, and the length of a time slot is 1 second. The mobile node is at locations 0, ..., 4 with probabilities 0.5, 0.2, 0.15, 0.10, and 0.05, respectively. The successful transmission probability is

**Algorithm 2** Algorithm to solve transmission optimization of a mobile node, energy management and optimal deployment of wireless power sources.

- 1: **repeat**
- 2: Select a set of candidate locations for wireless power sources to be deployed  $\mathcal{L}_D$
- 3: Obtain optimal thresholds of energy management for wireless power sources  $l \in \mathcal{L}_D$ , e.g., by using Algorithm 1
- 4: Obtain an optimal transmission policy by solving (21)-(25) given the wireless power sources at the candidate locations and thresholds of the energy management strategy, calculate loss probability given the optimal transmission policy, and ensure that the thresholds are in feasible region
- 5: **until** The set of deployed wireless power sources achieving the lowest total cost is found.

0.99 in all the locations. We consider the mobile node with a sensor which periodically performs sensing. The mobile node generates a new packet immediately after the packet generated earlier has been successfully transmitted or discarded due to reaching the delay deadline. The minimum throughput requirement is 0.01 packets per time slot for all the locations. In addition to the optimal transmission policy obtained from solving the CMDP model, we also consider “always transmit” and “always wait” policies for comparison. For the “always transmit” policy, the mobile node always transmits the packet if there is enough energy, i.e.,

$$\pi_{\text{at}}(\theta, \delta) = \begin{cases} 1, & e > 0 \text{ AND } \delta = 1 \\ 0, & \text{otherwise} \end{cases} \quad (48)$$

where  $\theta = (d, e, l) \in \Theta$ . For the “always wait” policy, the mobile node always waits and it transmits merely before the delay deadline is reached, i.e.,

$$\pi_{\text{aw}}(\theta, \delta) = \begin{cases} 1, & e > 0 \text{ AND } \delta = 1 \text{ AND } d = D - 1 \\ 0, & \text{otherwise.} \end{cases} \quad (49)$$

These policies can be applied to obtain the transition matrix in (28) and to derive the performance measures similar to those of the optimal policy obtained from the CMDP.

We assume that the wireless power source consumes one and zero unit of electricity power per time slot when it is active and inactive, respectively. Note that one unit of electricity power consumed by the wireless power source is different from one unit of energy harvested and used by the mobile node for packet transmission. The power cost is one monetary unit per power unit. For example, if the consumption of the active wireless power source is 1kW, then one unit of power per time slot (i.e., one second) is equal to  $1000/3600 = 0.27$  Wh. If the electricity price is 20 cents/1kWh, then one monetary unit is  $0.27 \times 20/1000 = 0.0054$  cents.

## B. Numerical Results

1) *Transmission Policy*: Figs. 4(a) and (b) show the optimal transmission policy when a mobile node is at locations 0 and 1,

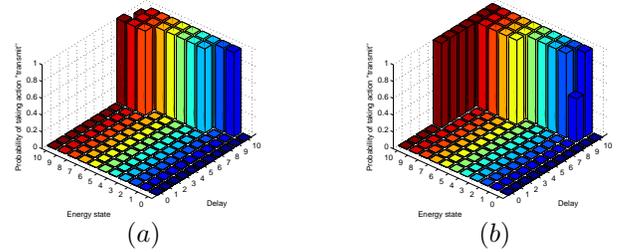


Fig. 4: Optimal transmission policy when a mobile node is in (a) location 0 and (b) location 1.

respectively. We observe that at different locations, the mobile node has different policies to transmit the packet according to the delay and energy states. However, they have similar trend. In particular, when the delay is large and energy level is high, the mobile node is likely to transmit the packet. This is also true for other locations 2-4, which we omit for brevity of the paper. The cause of this pattern in the policy is that the mobile node has to conserve energy for the future transmission, especially, in the location without any wireless power source. Therefore, the mobile node will wait until the delay deadline is almost reached and then transmit instead of transmitting the packet immediately. From the policies shown in Figs. 4(a) and (b), it is worth noting that there is no threshold policy [31] for the mobile node, as the constraint on the minimum throughput is imposed. Therefore, the optimal policy can be obtained only through solving the linear programming equivalent model.

2) *Impact of Energy Storage Capacity*: Then, the performances of the mobile node in terms of average transmission delay, probability of packet loss due to missing the delay deadline, and throughput are evaluated. Fig. 5 considers the performances when the energy storage capacity is varied. The comparison with the naive policies, i.e., “always transmit” and “always wait”, is also provided. For the average delay in Fig. 5(a), the “always transmit” policy achieves the lowest delay, while the “always wait” policy achieves the highest delay. Similarly, the “always transmit” policy achieves the largest throughput, while the “always wait” policy achieves the lowest throughput in Fig. 5(c). Even though the “always transmit” may be good in these performance metrics, it suffers from high loss probability (Fig. 5(b)). This unexpected result is due to the fact that the “always transmit” policy does not concern about the energy state and the mobile node will transmit as long as there is enough energy in the storage. Consequently, when the mobile node does not harvest energy for some period of time (e.g., when the mobile node stays at location 0), the mobile node will not have enough energy to transmit the packet, resulting in the high loss probability. The “always wait” policy achieves much lower loss probability, allowing the mobile node to harvest and accumulate energy in its storage for future transmission. When the energy storage capacity increases, the average delay and throughput of the “always transmit” and “always wait” policies are not observably affected. For the loss probability, it is slightly affected by the increase of energy storage capacity only.

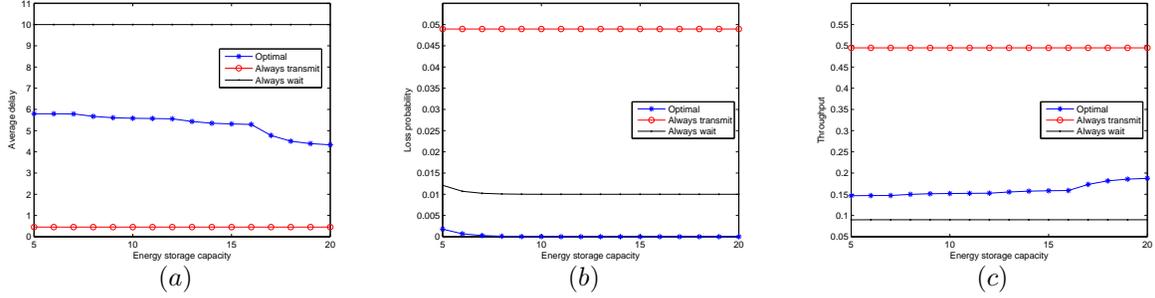


Fig. 5: (a) Average transmission delay, (b) loss probability, and (c) throughput under different energy storage capacities.

For the optimal policy, the loss probability is the lowest (Fig. 5(b)), which is the desirable performance. In addition, the optimal policy achieves better average delay than that of the “always wait” and better throughput than that of the “always wait”. Note that when the energy storage capacity increases, the average delay decreases and the throughput increases for the optimal policy. This is due to the fact that the mobile node has higher chance to keep energy in the storage and does not have to wait too long to transmit the packet. The loss probability slightly decreases when the energy storage capacity increases with the same reason.

Note that we observe the abrupt changes of the average transmission delay and throughput in Fig. 5(a) and (b), respectively, when the energy storage capacity is 16 units. This phenomenon is from the fact that the energy storage capacity is large enough to provide sufficient energy for the mobile node in most of the time. Therefore, when needed the mobile nodes can use such energy to transmit a packet, and consequently the average delay and throughput sharply decreases and increases, respectively.

3) *Impact of Delay Deadline*: Figs. 6(a), (b), and (c) show the performances when the delay deadline is varied. As the delay deadline increases, the average delay increases (Fig. 6(a)). The similar result is observed for the throughput (Fig. 6(c)). Again, the average delay and throughput of the optimal policy are between those of “always transmit” and “always wait” policies. As shown in Fig. 6(b), the optimal policy again achieves the lowest loss probability. Note that when the delay deadline decreases, the throughput decreases, since the mobile node has shorter time period (i.e., less opportunity) to transmit a packet successfully.

4) *Impact of Throughput Requirement*: Fig. 7 shows the performances when the throughput requirement is varied. As the throughput becomes a stricter constraint of the optimal policy, the mobile node has to transmit packet more quickly. As a result, the average delay and loss probability decrease significantly, while the actual throughput increases. However, although increasing the throughput requirement is beneficial, it may result in infeasible solution and the optimal policy may not exist. For example, based on Fig. 7, when the throughput requirement increases beyond 0.24, the feasible solution is not available.

5) *Impact of the Threshold (Minimum Required Number of Mobile Nodes to Activate Wireless Power Sources)*: Next, we consider the threshold-based energy management strategy of

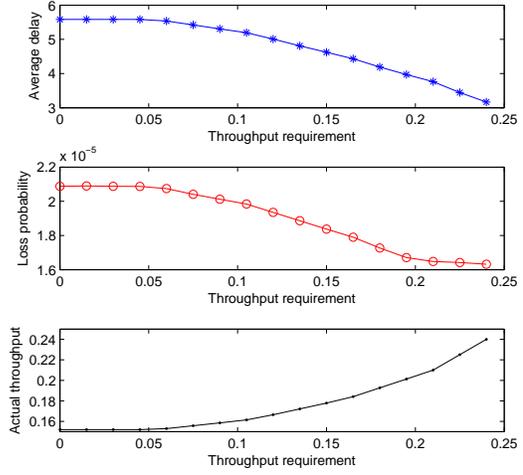


Fig. 7: Average delay, loss probability, and actual throughput under different throughput requirement.

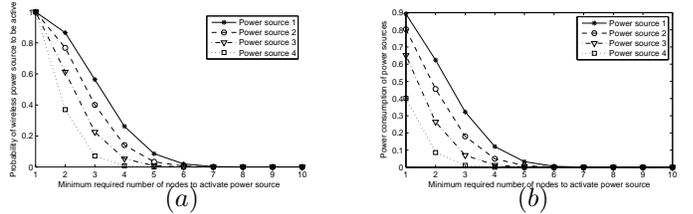


Fig. 8: (a) Probability of a wireless power source to be active and (b) power consumption when the threshold (i.e., minimum required number of mobile nodes to activate a wireless power source) is varied.

the wireless power source. The threshold is referred to as the minimum required number of mobile nodes to activate the wireless power source. Fig. 8(a) shows the probability of wireless power sources to be active when such number of mobile nodes is varied. When the threshold is small, the probability that the wireless power source will be active is high and this probability decreases as the threshold increases. This is due to the fact that there is lower chance that more number of mobile nodes will be in the harvesting coverage of the wireless power source.

It is observed that with the threshold-based energy management strategy of the wireless power source, the power source can reduce its power consumption by limiting the

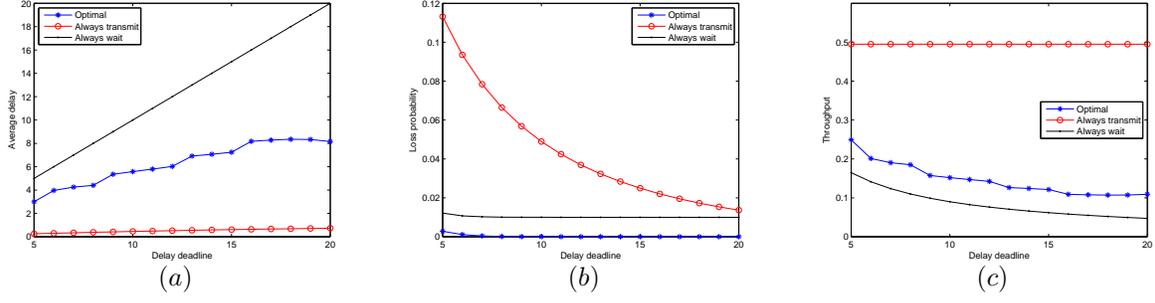


Fig. 6: (a) Average transmission delay, (b) loss probability, and (c) throughput under different delay deadline.

chance of releasing wireless energy needlessly. This result is shown in Fig. 8(b), in which the power consumption of each wireless power source decreases as the threshold increases. Although there is the energy conservation from this strategy, the performances of the mobile nodes could be negatively affected as the energy supplied will be lower.

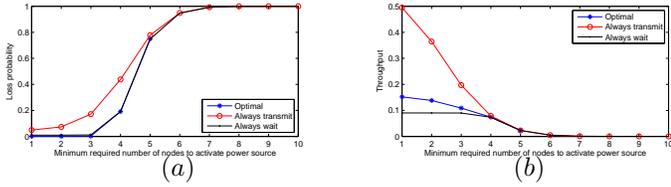


Fig. 9: (a) Loss probability and (b) throughput of a mobile node when the minimum required number of mobile nodes to activate a wireless power source is varied.

Figs. 9(a) and (b) show that loss probability increases and throughput decreases as the threshold of the wireless power source increases. The similar results are observed for optimal, “always transmit”, and “always wait” policies. This is due to the fact that the energy supply is lower for the larger threshold. From the results in Figs. 8(a), (b), Figs. 9(a), and (b), the threshold of the wireless power sources should be carefully chosen considering the tradeoff between power consumption and the mobile node’s transmission performance.

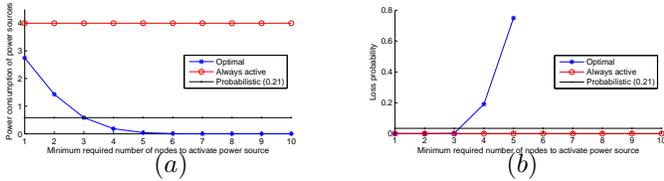


Fig. 10: (a) Power consumption and (b) loss probability of different energy management strategies.

Fig. 10 shows the power consumption and loss probability of different energy management strategies for the wireless power sources. Here, for the probabilistic strategy, the probability of the wireless power sources to be active is set to be 21% such that the total power consumption is equal to that of threshold-based strategy with 3 nodes to activate the wireless power sources. Clearly, the “always active” consumes the highest amount of power, which it achieves the same loss probability performance as that of the threshold-based strategy when the threshold is one. This is from the fact that the

threshold-based strategy activates the power sources one when there is a node in its harvesting coverage. For the probabilistic strategy, although the power consumption is the same as that of the threshold-based strategy when the threshold is three, the packet loss probability of the threshold-based strategy is much lower than that of the probabilistic strategy. Again, this is due to the fact that the power sources are activated only there are enough number of nodes in the harvesting coverage.

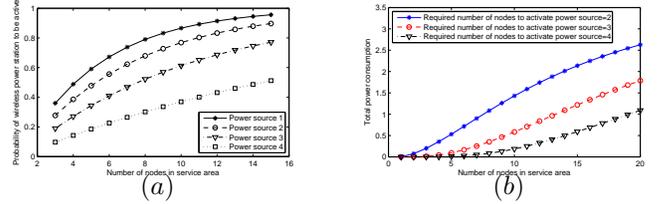


Fig. 11: (a) Probability of wireless power sources to be active and (b) total power consumption of all wireless power sources when the number of mobile nodes in a service area is varied.

*6) Impact of Number of Mobile Nodes in a Service Area:* Next, we consider the impact of when the number of mobile nodes in the service area is varied. With the threshold to activate the power sources to be 3, Fig. 11(a) shows that when the number of mobile nodes in the service area increases, the wireless power sources will be active more frequently. As a result, the total power consumption of all the wireless power sources increases (Fig. 11(b)). However, since there is more energy supply, the performances of the mobile nodes improve. Lower average delay, lower loss probability, and higher throughput are observed in Figs. 12(a), (b) and (c), respectively. These results suggest that the power consumption and transmission performance depend not only on the threshold of a wireless power source, but also the number of mobile nodes in the service area.

*7) Impact of Loss Requirement:* Next, we investigate the interrelationship between the threshold of a power source and loss requirement. We assume that wireless power sources 3 and 4 are not deployed, and the energy supply of the mobile nodes is from wireless power sources 1 and 2 only. Using Algorithm 1, Fig. 13 shows the feasible regions (i.e., sets) of the thresholds (i.e., minimum required numbers of mobile nodes to activate wireless power sources 1 and 2) such that the loss requirement can be met. Clearly, when the loss requirement is tighter (i.e., 0.01), the feasible threshold is smaller, which makes sure that wireless power sources will

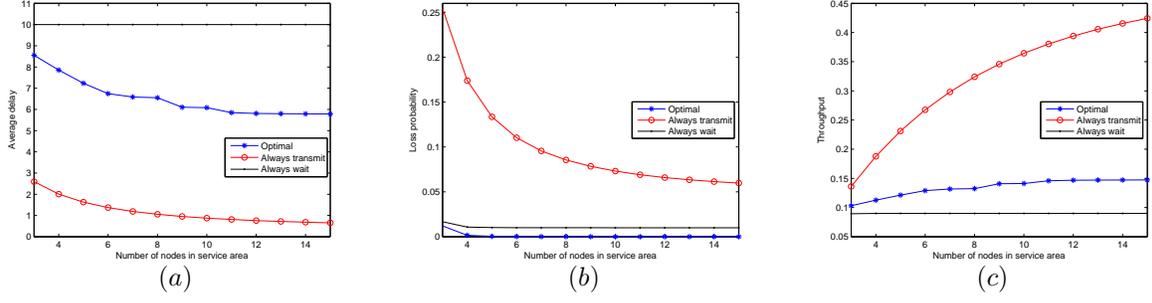


Fig. 12: (a) Average transmission delay, (b) loss probability, and (c) throughput under different number of mobile nodes in a service area.

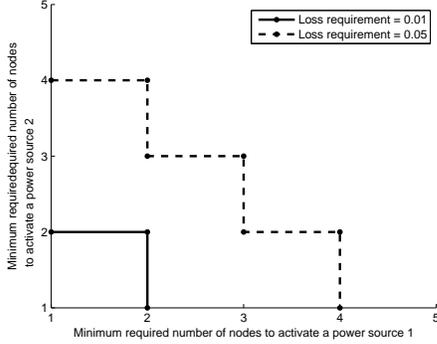


Fig. 13: Number of mobile nodes to activate wireless power sources 1 and 2 such that loss requirement is met.

release sufficient wireless energy to the mobile nodes. Given the tradeoff between power consumption and transmission performance, the thresholds can be chosen from the feasible region to minimize the total power consumption of all power sources.

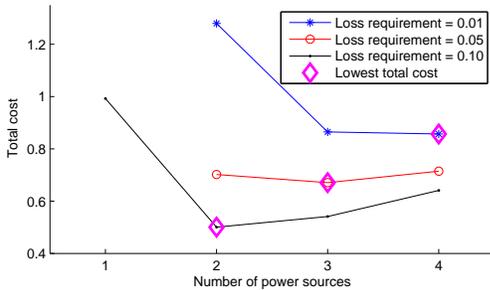


Fig. 14: Total cost under different number of wireless power sources.

8) *Wireless Power Source Deployment*: Next, we consider wireless power source deployment. We set the cost of deployment per time slot to be 0.1 monetary units (i.e., the lump-sum deployment cost divided by the entire operational duration of a wireless power source). Fig. 14 shows the total cost (i.e., deployment cost plus total power consumption cost) per time slot, when the number of wireless power sources to be deployed is varied. With different loss requirement, there is the optimal number of wireless power sources to be deployed such that the total cost is minimized. Note that for the tight loss requirement (i.e., 0.01 and 0.05), having one wireless power

source is not sufficient to meet the loss requirement. Therefore, the total costs of such cases cannot be shown.

## VII. CONCLUSION

With the wireless energy harvesting or wireless power transfer capability, mobile nodes can operate and replenish their energy storage even while they are moving. In this paper, we have considered the mobile nodes with wireless energy harvesting. The mobile node is to transmit data packet with a strict delay deadline. We have first considered the optimal transmission policy of the mobile node. The energy storage of the mobile node can be filled wirelessly when the mobile node moves into the harvesting coverage of a wireless power source. We have obtained the optimal transmission policy by formulating and solving the constrained Markov decision process model. Next, we have addressed the energy management strategies of the wireless power sources. Three distributed strategies have been discussed where we have focused on the threshold-based strategy. In this strategy, the wireless power source is active when the number of mobile nodes in its harvesting coverage is equal to or larger than a threshold. The analysis in terms of feasible region and optimal thresholds to minimize the power consumption has been presented. Finally, we have considered the wireless power source deployment issue. The results from the optimal transmission policy (i.e., to minimize the loss probability due to delay deadline violation) and threshold-based energy management strategy can be used to determine the best deployment setting of the wireless power sources to minimize long-term cost.

For the future work, the energy management strategy of the wireless power sources can be made specific to mobile nodes. For example, the wireless power sources could be activated by a particular set of mobile nodes only to ensure that their performance will be maintained above the target level.

## APPENDIX EXTENSION OF OPTIMIZATION FORMULATION

In the following, the CMDP model can be extended to consider the performance at different locations. These extensions require that the mobile node can transmit a packet at any location.

### A. Location Specific Throughput Constraint

The optimization problem based on CMDP and LP models presented in (19)-(20) and (21)-(25), respectively, can be extended by considering the required throughput requirement at each location. In this case, the constraint in (20) is modified as follows:

$$\text{s.t.} \quad \mathcal{I}_{T,l}(\pi) \geq T_l \quad (50)$$

where  $T_l$  is the throughput requirement at location  $l \in \mathcal{L}$ . Then, the constraint in (22) becomes

$$\text{s.t.} \quad \sum_{e=0}^E \sum_{d=0}^D \sum_{\delta \in \Delta} \phi((e, d, l), \delta) \Upsilon((e, d, l), \delta) \geq T_l, \quad \forall l \in \mathcal{L}. \quad (51)$$

### B. Balancing Performance at Different Location

The objective function defined in (19) of the original CMDP formulation is to minimize total loss probability of the node. However, it does not balance the performance (i.e., loss probability) at different locations. We can consider an alternative formulation, which tries to minimize the maximum loss probability among all locations. The corresponding CMDP model is given as follows:

$$\min_{\pi} \max_{l \in \mathcal{L}} \mathcal{I}_{L,l}(\pi) \quad (52)$$

$$\text{s.t.} \quad \mathcal{I}_T(\pi) \geq T. \quad (53)$$

Accordingly, the LP model can be modified to consider this min-max objective. Specifically, an auxiliary variable  $\rho$  is used to determine the highest loss probability at any location. The LP model becomes

$$\min_{\phi(\theta, \delta)} \rho \quad (54)$$

$$\text{s.t.} \quad \sum_{e=0}^E \sum_{d=0}^D \sum_{\delta \in \Delta} \phi((e, d, l), \delta) \Lambda((e, d, l), \delta) \leq \rho, \quad \forall l \in \mathcal{L} \quad (55)$$

$$(22), (23), (24), (25)$$

$$\rho \geq 0. \quad (56)$$

Similarly, the location specific throughput constraint can also be included.

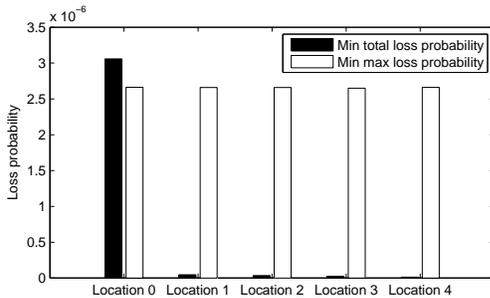


Fig. 15: Loss probability comparison between minimizing total loss probability and minimizing maximum loss probability.

With the same parameter setting as that in Section VI, Fig. 15 shows the loss probability performance with the

comparison between the solutions from CMDP models with the objectives to minimize total loss probability and to minimize the maximum loss probability among different locations. Although the former (i.e., (19)-(20)) can achieve the lower total loss probability in all locations, some location may suffer from high loss probability (i.e., location 0). Such a location is where the wireless power source is not available. However, the latter (i.e., (52)-(53)) can balance the loss probability in all the locations, yielding better result in terms of fairness. This is achieved by the mobile node conserving energy from wireless power sources for the packet transmission at the location without power supply.

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**Ping Wang** (M'08) received the PhD degree in electrical engineering from University of Waterloo, Canada, in 2008. She is currently an assistant professor in the School of Computer Engineering, Nanyang Technological University, Singapore. Her current research interests include resource allocation in multimedia wireless networks, cloud computing, and smart grid. She was a corecipient of the Best Paper Award from IEEE Wireless Communications and Networking Conference (WCNC) 2012 and IEEE International Conference on Communications (ICC) 2007. She is an Editor of *IEEE Transactions on Wireless Communications*, *EURASIP Journal on Wireless Communications and Networking*, and *International Journal of Ultra Wideband Communications and Systems*.



**Dusit Niyato** (M'09) is currently an Associate Professor in the School of Computer Engineering, at the Nanyang Technological University, Singapore. He received Ph.D. in Electrical and Computer Engineering from the University of Manitoba, Canada in 2008. His research interests are in the area of the optimization of wireless communication and mobile cloud computing, smart grid systems, and green radio communications.