Optimizing Energy Consumption in Terahertz Band Nanonetworks

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***Abstract*—In this paper, we develop a technique for achieving the maximum utilization of harvested energy in perpetual wireless nanonetworks, where nanonodes communicate in the THz frequency band. Because of their nano-scale sizes, nanonodes cannot store large amounts of energy. Compounding the problem, the arrival of energy is not constant, but follows a stochastic process. Therefore, an optimum design for the consumption of this limited amount of energy is required. We model the problem as a Markov decision process, where we include the energy for both reception and transmission of packets. We analyze the performance of the energy harvesting and consumption processes for very low energy harvesting rates and small energy storage capacity. We compare the performance of the optimal policy with intuitive energy consumption policies. Next, since solving an optimized problem of this sort is too compute-intensive for nanonodes with limited resources, we propose a light-weight heuristic method that can perform close to optimal. Simulation results show that our heuristic model and the optimal model can serve as a framework for the design of nanonodes that operate in low rate stochastic energy harvesting conditions with limited energy storage.**

***Index Terms*—Nanonetworks, terahertz, energy harvesting, optimization, energy consumption.**

I. Introduction

NANOTECHNOLOGY advancement promises to provide a significant rise in small scale communication. Wireless nanonetworks [1], [2] are a new generation of networks at nano-scale, which are envisioned to be produced in the coming years. A basic nanonode is composed of a nano-antenna, nano-memory, a nano-processor, nano-sensors, and energy storage. Each nanonode is in the range of micro to nano meters in size. The nanoscale property of nanonodes opens the door for exciting new applications in the biological, medical, chemical, environmental, military, and industrial domains [2].

Nanonodes need to communicate to control or actuate an action, or similarly monitor a phenomena. In other words, they will need to communicate between themselves as well as with nodes in the micro and macro domain. Among several possible communication methods (molecular, optical, acoustic and electromagnetic) [1] for nanonodes, we focus on the communication mechanism in the 0.1–10.0 terahertz frequency band. However, models and concepts developed here can be generalized to other communication mechanisms (particularly optical and acoustic communication).

Communication requires energy, and as tiny nanonodes will have a very limited energy storage capacity [3], energy harvesting techniques will need to be deployed. Nanoscale harvesting elements, such as nanowires [4] or biofuel cells [5], which enable harvesting from various resources such as vibration or blood sugar, have been proposed. Harvested energy would be stored for a short period of time before consumption. Due to the size limitations of nanonodes, it can take several seconds to harvest energy which is then consumed in nanoseconds [3]. Therefore, the optimum consumption of this limited and precious energy is a major challenge on the road to the realization of nanonetworks.

The problem of optimizing the consumption of harvested energy is not only difficult because of the small scale of energy storage and the amount of harvested energy, but also because of properties of the harvesting process. The utilization of harvested energy is challenging because the intensity of available energy has a stochastic behavior. Therefore, solving the problem of maximizing the utilization of harvested energy plays a major role in the design of perpetual nanonetworks. The utilization is achieved through optimizing communication energy inasmuch as the energy for communication comprises the major portion of energy consumption for a nanonode. Thus, we must design the energy consumption rate (i.e., transmission and reception rate of data) in such a way that the probability that the nanonode does not have energy to communicate in the future is minimized while the data rate is maximized.

This paper investigates the energy consumption allocation problem that aims to maximize the data rate in a limited energy storage capacity condition, where the energy arrivals follow a random process. We summarize our four main contributions here: (I) Previous efforts consider only the transmission rate as the consumption rate to be optimized. However, we believe a model which includes the energy for reception is required. (II) In most previous models, it is assumed that in each time slot, the amount of harvested energy would be enough for at least one transmission. This is not a valid assumption in many situations when the harvesting rate is very low and it may take multiple timeslots to accumulate enough energy for just one transmission. In this work, we study the effect of low harvesting rates. (III) We evaluate the performance of a nanonode when it has a limited energy storage capacity. This is an important factor for nanonodes where their size limitation does not allow them to have large energy storage. (IV) Finally, solving an optimal model on the resource-limited nanonodes is not possible. Also, keeping a solved solution may not be

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the best approach because a change in any of the model's parameters means a new solution needs to be found. Therefore, we develop a light-weight heuristic method which performs near the optimal point and would not require heavy processing load on a nanonode.

Due to differences between the nanoscale and microscale paradigms, previous optimization models of harvested energy are not applicable to the nanoscale problem. Most previous work at the microscale does not include the characteristics of the energy harvesting process, energy storage, and processing capability of nanoscale devices in their models. In the domain of nanonetworks, an initial model of energy consumption and harvesting has been proposed [3]. However, the model does not the optimize the consumption of energy. In our previous work [6], we investigated the optimization of energy consumption for packets. We developed a multi-objective optimization problem to find the best packet size to exploit the trade-off between energy consumption, transmission delay, and communication reliability. However, the scheduling of packets to utilize the harvested energy has not been addressed, but will be investigated in this work. We also designed a receiver-initiated energy harvesting-aware MAC protocol (RIH-MAC) for packet exchange between nanonodes [7]. RIH-MAC is distributed and could be integrated with a packet scheduling technique such as one we propose here.

In the remainder of this paper, we first overview literature on energy optimization in Section II. Next, we introduce our problem formally in Section III. Section IV follows with the introduction of some basic schemes for energy consumption. In Section V, we formulate the problem of consumption rate allocation as a Markov decision process (MDP), which can find the optimal scheme to maximize the data rate. We follow this with an analysis of the energy storage capacity, harvesting process, and data rate utilization. This analysis with the basic schemes inspires the development of light-weight heuristic schemes in Section VI. The performance of the designed schemes is evaluated in Section VII. Finally, the paper is concluded in Section VIII.

II. Related Work

Optimizing the consumption of harvested energy for communication has been a popular topic of research in recent years [8]–[12]. Kansal *et al.* [8], as one of the initial efforts in this domain, developed a model to evaluate the process of energy harvesting and consumption. They mainly focus on modeling the energy consumption and harvesting process for sensor nodes without optimizing the consumption. The next step, which has been considered in later work (e.g., [9]–[17]), focuses on the optimization of the problem. The general solution approach is to find the trade-off between the loss of energy (to utilize throughput) and one or several quality of service metrics (e.g., packet loss, delay). Since energy arrival is a random process, research has mainly taken two approaches to address this problem.

In the first approach, most of the work, such as [12], [16], does not explicitly include the stochastic behavior of energy harvesting in their modeling. They assume that they can develop a prediction method such as exponentially weighted moving average (EWMA) to predict the amount of available energy in upcoming slots.

The second approach is explicitly to include the random properties of energy harvesting in modeling and optimization. Yang and Ulukus [17] investigate the optimal packet scheduling problem for a single-user energy harvesting system, where both the data packets and the harvested energy follow stochastic arrival. They develop a scheme to adaptively change the transmission rate based on the traffic load and available energy required to minimize average packet delivery time. They assume that the energy harvesting times and harvested energy amounts are known. Therefore, they could develop optimal off-line scheduling policies. Tutuncuoglu *et al.* [10] investigate optimal schemes for wireless transmission when channel fading exists. They evaluate two objective functions: maximizing the throughput and minimizing the transmission completion time. They solve the problem in both deterministic and stochastic settings. Furthermore, they analyze the processes of energy harvesting and consumption to find heuristic methods which can have optimal performance. A common approach for utilizing the harvested energy, which we also use, is to model the optimum energy consumption problem as Markov decision processes to maximize a utility function, e.g., [9], [13], [18]. These methods try to maximize a utility function while considering other functions such as wireless channel conditions.

Previous work for optimizing energy consumption is not applicable to nanoscale networks. First of all, models assume that energy storage capacity is infinite or extremely large. In nanonetworks, it is envisioned that the energy storage capacity will be very limited [3] where nanonodes will have only enough energy storage for the communication of several hundred bits. Second, in the previous models, the energy for reception is not considered. This assumption is valid when the reception energy is much lower than the transmission energy or in RFID networks, where a node exploits the energy of received packets for transmission. Another example could be single hop communication, where for each reception, a node either does not transmit or sends only one transmission (request-response model). However, in nanonodes, which will most likely operate in a multi-hop fashion with several neighbors, reception can be significant, especially when the energy budget is very limited. Third, in previous work, the harvesting rate is assumed to be very close to the consumption rate. This is not valid for nanonetworks, where for example it can take 10 seconds to have energy for the transmission of only a couple hundred bits [3]. Finally, most optimal models are either valid for very limited scenarios, which are not useful if any of the parameters are changed, or they are too compute-intensive to be run on nanonodes. Therefore, new schemes such as heuristic light-weight methods, similar to ones which we develop in this work, are required.

III. System Model

In this section, we introduce our notation for the combined process of energy harvesting and energy consumption at a nanonode that is part of an *ad hoc* nanonetwork. Each nanonode transmits its own data as well as receives and forwards its neighbors' data. The particular reception and forwarding schemes are out of scope for this work. Also the details of protocols for the communication among nanonodes are not part of this work. In our other work [7], we designed a receiver-initiated harvesting-aware MAC protocol (RIH-MAC) for packet exchange between nanonodes.

Energy harvesting follows a random variable, while energy consumption is defined based on a set of available actions on how much energy is to be consumed. Later, several schemes are developed to control the process of energy consumption, i.e., select the action for each state of energy based on various objectives. Various schemes are described in Sections IV–VI.

We consider a discrete time model, in which time is slotted into intervals of unit length. In each slot, some energy is harvested and added to the energy storage, and similarly some energy is consumed and deducted from the energy storage based on the consumption scheme. We assume that the energy storage is ideal and there is no significant leakage. The amount of harvested energy follows a random process.

We denote the system states by $S = S_1, S_2, \cdots, S_s$, where $s = C + 1$ for energy storage of capacity $C \cdot E_{min}$ units of energy. The value of E_{min} denotes the unit of energy, e.g., 1 pJ. The first state (S_1) is called the *out of energy* state, where there is no energy for communication. The last state (S_s) is called the *full energy* state, where there is no capacity to store new energy arrivals. Being in either *out of energy* state or *full energy* state is not desirable because it means the loss of packet receptions (due to lack of energy) or loss of harvested energy (due to lack of storage), respectively.

The energy generation process of the node is modeled by a random process, denoted as an i.i.d. random variable H. We discretize H to take one of the discrete values $[h_0, h_1, \cdots, h_D]$ with probability $p = [p_0, p_1, \cdots, p_D]$. The h_i indicates the amount of energy harvested and p_i is defined as

$$p_i = F_H(h_i) - F_H(h_{i-1}), \quad h_{-1} = 0,\ h_i > h_{i-1}. \tag{1}$$

The value of D is determined based on the requirement that p_i is always greater than the threshold δ and $F_H(h_i) \le \delta_2$, where $\delta \in \mathbb{R}(0, 10^{-pp}]$, $\delta_2 \in \mathbb{R}[1 - 10^{-pp}, 1)$ for pp digits of accuracy. The value of h_0 can take both zero and nonzero values. If $h_0 = 0$, then $p_0 = 0$. This means that always some energy will be harvested. In some scenarios, the amount of harvested energy may be lower than one unit of energy (E_{min}). In this case, $h_0 > 0$ and $p_0 > 0$.

Since the differences between the h_is need not necessarily to be equal, this mapping applies for both linear and nonlinear storage. In the simplest form, for linear storage, harvested amounts in $[h_{i-1}, h_i)$ represent that $i \cdot E_{min}$ units of energy are harvested. For example, the value of p_2 represents the probability that two units were harvested. This means that the system will move from arbitrary state S_m to state $max(S_{2+m}, S_s)$, with the assumption of no energy consumption during the same slot.

The unequal differences between value of the h_is can also represent the units of energy for nonlinear storage. This can be done by applying a nonlinear function to the random variable H, which still produces a random variable [19]. Nonlinear storage is often found in capacitor storage, e.g., [3], [18].

It is assumed that there are always packets ready for transmission. The transmission and reception of each packet will consume E_{tx} and E_{rx} units of energy, respectively. We assume the energy consumed for listening and idle modes is negligible, based on previous studies [3], [20]. The consumption strategy of a nanonode, i.e., the number of transmissions and receptions per slot, is denoted as scheme π. The action taken by a node in a time slot is denoted as $a_{(i,j)}$, $i, j \ge 0$, which is selected from $A = \{a_{(0,0)}, a_{(1,0)}, a_{(0,1)}, a_{(1,1)}, \cdots, a_{(m,n)}, a_{(m+1,n)}, a_{(m,n+1)}, a_{(m+1,n+1)}, \cdots\}$. The action $a_{(i,j)}$ corresponds to the reception of i and transmission of j packets in the time slot, where the sum of the energy consumption, denoted as E_k, cannot exceed the maximum consumption per slot, E_c, $0 \le E_c \le C$, i.e., $i \cdot E_{rx} + j \cdot E_{tx} \le E_c\ \forall i, j$. We denote S_A as the number of members of A. The minimum S_A is 3, which corresponds to $A = \{a_{(0,0)}, a_{(1,0)}, a_{(0,1)}\}$, and consequently $E_c = \max(E_{tx}, E_{rx})$. For the simplicity of presentation, we consider the total energy consumption for both transmissions and receptions as E_k with the corresponding a_k, $1 \le k \le S_A$. Without loss of generality, we assume that the actions of A are ordered ascending based on their E_k values. We assume that there is a mechanism in which a nanonode can enforce the number of receptions. This can be an independent mechanism by each node or can be a synchronized mechanism between transmitters and receivers. The simplest mechanism is just to disable the communication module for some period of time, during which the nanonode does not want to receive packets. Details of how to decide the times for disabling the communication module are out of scope of this work.

Although the model is general, the focus of this work is for scenarios where the consumption rate is faster than harvesting rate. Therefore, it means that several units of energy are consumed per packet transmission or reception. Likewise, several packets can be exchanged in one time slot. Note that this action set definition can cover multiple packet communication situations. For example, $a_{(0,2)}$ can represent the transmission of one packet with twice the amount of energy, as well as the transmission of two packets. Nevertheless, for simplicity we assume that $a_{(i,j)}$ maps to i receptions and j transmissions. Before describing our optimal scheme, we first introduce some basic schemes.

IV. Basic Schemes

In this section, we describe some basic consumption schemes that are intuitive and common in the literature [9], [21]–[23]. They will be used later to compare with our optimal and heuristic schemes. Also, they will help in designing the heuristic schemes.

- **Aggressive (Agg)**: In this scheme, the highest possible consumption action, based on the amount of available energy, is always selected. This method tries to achieve the highest data rate. However, it will result in the *out of energy* situations most of the time.

TABLE I
SCHEMES COMPARISON—(H)IGH, (M)EAN, (L)OW

Metric	Agg	Con	C-H	Mean	Rand
p(o)	H	L	L	M	M
p(f)	L	H	H	M	M
EU	H	L	M	M	M

- **Conservative (Con)**: In this scheme, one of the lowest consumption rates, i.e., $a_{(1,1)}$, $a_{(0,1)}$, $a_{(0,1)}$, or $a_{(0,0)}$, is selected based on the availability of energy. With this scheme, there is always some energy left, but the data rate as well as the utilization of energy is very low.
- **Consume-Harvest (C-H)**: In this scheme, consumption is selected based on the amount of energy which has just been harvested in the previous time slot. More specifically, it will choose the action with the amount of energy closest to the amount of just harvested energy. This scheme is expected to behave better than the conservative scheme in terms of data rate. However, there is the chance of falling to the *full energy* state because in many time slots the amount of harvesting may not be enough to transmit or receive any packet, but it will result in the accumulation of energy units.
- **Mean**: In this scheme, the average action, which is a_k, $k = \left\lfloor \frac{S_A}{2} \right\rfloor$, is selected. If there is not enough energy to select the average action, then the closest action is chosen. The performance of this scheme would be between the conservative and aggressive schemes.
- **Random (Rand)**: This scheme selects an action randomly from the set of actions. If the energy for the chosen action is above the current energy level of storage, the random selection process is repeated. The behavior of this scheme cannot be predicted exactly. In general, it is expected that it will have an average performance in the long-term.

The evaluation of these basic schemes reveals that they cannot achieve the maximum utilization of energy while avoiding going to the *full* or *out of energy* states. Table I compares these basic schemes in a general view without going into details of evaluation and results, which will be described later in Section VII. Table I reveals that none of the schemes performs well in all metrics. In fact, they cannot satisfy and balance these metrics at the same time. Therefore, there is a need to develop an optimal model. In fact, a model with a low chance of being in the *full*$(p(f))$ or *out of energy*$(p(o))$ state while having high energy utilization (EU) is required.

V. Optimal Model

The problem of assigning the optimal action (i.e., number of transmissions and receptions) per slot can be described as a Markov decision process as follows.

The system model is as defined in Section III. The probabilities of transferring between states depend on the current state, the amount of energy harvested, and the action taken. Actions are selected from the set A. Formally, state transitions can be written as

$$P(S_i, S_j, a_k) = p_u, \quad \sum_{x=1}^{s} P(S_i, S_x, a_k) = 1, \ 1 \le i, j \le s,$$

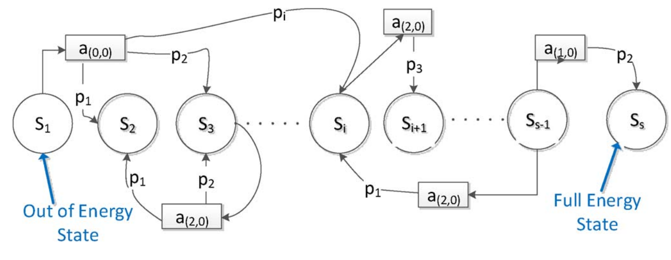

Fig. 1. A partial MDP (states and some actions are represented)—E_{min} is set to E_{rx}.

and j is specified as $j = i + h_u - E_k$, $E_k < i$, $i + h_u \le s$, $0 \le u \le D$, $1 \le k \le S_A$. The value of j represents the energy state after the harvesting of h_u units and consumption of E_k units of energy for action a_k taken. The condition $E_k < i$ limits the actions which can be taken to avoid consuming more energy than is harvested and stored. The condition $i + h_u \le s$ limits the harvested energy to the available capacity of energy storage. When $j = 1$, the system falls into the *out of energy* state, i.e, the node has consumed all of energy that it has stored and harvested. When $j = s$, the system falls into the *full energy* state, i.e., even after consumption, the system has stored and harvested up to the capacity C.

Fig. 1 illustrates some states, actions, and transitions between states. We note that this is not a full MDP diagram, but just serves as an illustrative example. Assume the node begins in state S_1 (*out of energy*). It will take action $a_{(0,0)}$ because there is no energy for either transmission or reception. Thus, the state it transits to is only dependent upon the amount of energy harvested. Assuming linear storage an that each state represents the energy for one additional reception with probability p_1 the system will harvest one unit of energy and move to state S_2. With probability p_2 it will harvest two units of energy and move to S_3. If the system is in state S_3 and takes action $a_{(2,0)}$ (two receptions which consume two units of energy), with probability p_1 it will harvest one unit of energy and move to state S_2, and with probability p_2 it will harvest two units of energy and remain in state S_3.

The reward function is defined in a way to maximize the utilization of energy, i.e., higher data rate, while satisfying the *packet balance* between reception and transmission. Maximizing the utilization of energy is a well-known metric [15], [18]. It also can be directly used as a metric for delay performance [15]. In addition to maximizing the utilization of energy, our model includes the packet balance between the number of packet receptions to the number of packet transmissions. As mentioned before, the energy for reception can be significant when a limited amount of energy exists, as well as when the number of transmitting neighbors becomes large. Therefore, we define our reward function to include the packet balance as well as energy utilization.

A. Maximizing the Energy Utilization

Maximizing the utilization of energy is directly related to moving between states. If the action is taking the system to a state with a higher level of energy, this poses negative rewards, i.e., energy has not been utilized. Recall that we assume that there are always packets ready to transmit. Therefore, not utilizing available energy means that packets that could be sent are not transmitted due to not taking the appropriate action for the current state. On the other hand, if the action is taking the system to a state with a lower level of energy, a positive reward will be given. Also, the reward for going to the first and last states should be significantly lower than other rewards. This is defined to avoid letting the energy level become zero or full. Being in the *out of energy* state causes the loss of packet receptions due to lack of energy. Likewise, being in the *full energy* state results in the loss of energy reception due to lack of empty space in storage.

The transition function between states, which is directly related to the utilization of available energy, is defined as the following function

$$J(S_i,S_j,a_k)=\begin{cases} i-j & j\neq 1,s \\ -(s+1) & j=1,s. \end{cases}$$

The function J simply defines positive values on more consumption of energy (utilizing energy) and negative values on the more harvesting of energy (not utilizing energy). Moreover, any transition to the first or last states receive a negative value. Although this function does not measure the utilization of energy directly, it satisfies as a function for our MDP model. Energy utilization EU for any point T along time can be formally defined as

$$EU=\frac{\sum_{t=0}^{T}E_t}{\sum_{t=0}^{T}H_t},$$

where E_t and H_t are the amounts consumed and harvested at timeslot t, respectively. EU has values in [0,1].

B. Balancing Packets

Balancing between the number of receptions and transmissions is required for several reasons. First, if a packet balance is not defined, the MDP solution may lead to only transmissions or only receptions, which is not desirable. Second, always having a fair distribution of energy between transmission and reception in an *ad hoc* network is required to balance between the transmission of a node's data versus forwarding neighbors' data. The target packet balance B_D is defined as the ratio between the number of packet receptions to the number of packet transmissions. The target *packet balance* is an application-dependent parameter, which may vary based on the number of neighbors, routing scheme, etc.

An *action balance* for action a_k, $1\leq k\leq S_A$, is

$$B_{a_k}=\begin{cases} \frac{a_{k_r}}{a_{k_t}} & a_{k_t}\neq 0,\ a_{k_r}\neq 0 \\ \varepsilon & a_{k_t}=0,\ a_{k_r}=0 \\ \frac{1}{E_k} & a_{k_t}=0 \text{ or } a_{k_r}=0, \end{cases}$$

where a_{k_r} and a_{k_t} represent the number of receptions and the number of transmissions for action a_k, respectively. The maximum value of B_{a_k} is denoted as B_{max}. Recall E_k is the amount of energy consumption for action a_k. For an action with no consumption, ε is selected as a very small value, e.g., $0<\varepsilon\leq 0.1$, which shows that this action does not affect the packet balance.

Then, the similarity function L of the action's balance B_{a_k} to the target balance B_D is defined as

$$L\left(B_D,B_{a_k}\right)=\begin{cases} \left|B_D-B_{a_k}\right|^{-1} & B_D\neq B_{a_k} \\ \frac{B_{max}}{\varepsilon} & B_D=B_{a_k}. \end{cases}$$

When the action has the maximum similarity with the target balance B_D, it will take a large value. Otherwise, the similarity is related to the proportional ratio of action receptions and transmissions to the target balance.

C. Reward Function

Finally, the reward function is formally defined as

$$R(S_i,S_j,a_k)=J(S_i,S_j,a_k)\cdot L\left(B_D,B_{a_k}\right).$$

This reward function implies that the total average reward is given to the highest average data rate, which is achieved via maximizing the utilization of available energy for harvesting. Moreover, it favors the actions which try to achieve the target packet balance.

D. Solution for Non-Stochastic Scenario

In this section, we look at a scenario, where we have *a priori* knowledge of the amount of harvested energy. Assume that all the harvesting values in the timeslot between $[0,T]$ are known at time 0. We also relax the conditions of avoiding going to the *out of energy* or *full energy* states. Then, the problem of maximizing energy utilization can be written as follows.

$$U_k(S_i)=\max\sum_{t=0}^{k}E(t), \tag{2}$$

where $E(t)$ represents the amount of energy consumption in each slot.

The behavior of this function has been presented as the curve under the stair case of harvested energy in [17]. It is shown that the closer $E(t)$ is to the amount of energy harvested, the better policy will be selected. Finding the solution in continuous time and continuous power consumption function has been studied in previous work, e.g., [10], [15]–[17].

In our scenario, we are dealing with discrete time units. Moreover, because the actions are selected from a set of actions, the power consumption function does not take continuous values. In addition, in an extended scenario, we include a balance factor, which limits the actions that can be selected. The balance function can be defined as

$$Bal_k=\min\left(B_D-\sum_{t=0}^{k}\frac{N_{rx}(t)}{N_{tx}(t)}\right), \tag{3}$$

where N_{rx} and N_{tx} correspond to the number of receptions and the number of transmissions for E_t energy consumption at one slot, respectively.

It is not trivial to trace the solution to this problem. Therefore, we limit our discussion and move to a solution for the stochastic scenario.

E. Solution for MDP

We solve this MDP through the value iteration method [24]. Let $V(S_i)$ be the value for each state, $i \in 1 \ldots s$. At the end of the solution by the optimal policy Π, $V(S_i)$ will represent the discounted sum of the rewards to be earned (on average) by using that solution for state i. The iterative steps are calculated based on

$$\pi(S_i) := \operatorname*{argmax}_{a_k} \left\{ \sum_{S_j} P(S_i, S_j, a_k)(R(S_i, S_j, a_k) + \gamma V(S_j)) \right\},$$

$$V(S_i) := \sum_{S_j} P(S_i, S_j, \pi(S_i))(R(S_i, S_j, \pi(S_i)) + \gamma V(S_j)),$$

where γ is the discount factor. After substituting the calculation of $\pi(S_i)$ into the calculation of $V(S_i)$, the combined step would be

$$V(S_i) := \max_{a_k} \left\{ \sum_{S_j} P(S_i, S_j, a_k)(R(S_i, S_j, a_k) + \gamma V(S_j)) \right\}.$$

This is repeated until the results converge.

The behavior of the MDP solution can be roughly described as follows. For a specific harvesting rate, the states of the system could be categorized into three main categories: (I) states close to the *out of energy* state; (II) states close to the *full energy* state; and (III) states in between. In the first category of states, the actions will try to stabilize the system to avoid going to the *out of energy* state. Similarly, in the second category of states, the actions will try to avoid going to the *full energy* state. They can safely go to one of the states in third category. The optimal actions for the third category of states would be to stay in their own category or at most move to one of the first category states. It is better to move towards the *out of energy* state than to be conservative and go to the *full energy* state because this way the energy utilization will be maximized.

F. Analysis of Markov Decision Process

The energy storage capacity of the system is the main parameter that determines the number of states. Therefore, we evaluate it here in more detail. This analysis will also provide a better understanding of the MDP to develop our heuristic methods in Section VI.

First, we evaluate the lower bound of the amount of energy storage, C, required to avoid going to the *full energy* state. In this analysis, we consider linear storage. Recall that H was the random variable for the harvesting with its distribution F_H. For simplicity, it is being discretized into D parts based on the unit of energy for linear storage. Then the MDP is defined, where the number of states were defined as $s = C + 1$. Assume C is less than D. Thus, s is equal to D at most. Now, consider the following scenarios:

I) The system is in the first state, i.e., out of energy state. Clearly, the optimal action for first state is no consumption, $a_{(0,0)}$. Then assume energy arrives with probability p_D, i.e., D units of energy have been harvested. It means that there is a jump from state 1 to state $D+1$. However, there is no such state because we assume that there are only D states. This implies that C should be larger or equal to D to avoid going to the *full energy* state.

II) The system is in any other state except the first state. Let us assume that the system is in arbitrary state i and the associated optimal action is a_k. The maximum amount of energy that action a_k could consume is E_c. This means that the minimum jump with an arrival of D units of energy from state i towards the *full energy* state would be $D - E_c$, and that the minimum capacity should be $i + D - E_c$. There are two cases here:
   - $E_c < D$ which does not provide a bound.
   - $E_c \geq D$ which is more likely to happen. This way, there would not be any chance of moving to the *full energy* state.

   As a result, the minimum value of D would be a lower bound for capacity. We call this the minimum lower bound for energy storage capacity to avoid going to the *full energy* state.

A similar reasoning applies for the *out of energy* state. In fact, for an arbitrary state i, the maximum jump toward the *out of energy* state occurs when energy arrives with p_0, i.e., no energy arrival, and the consumption is the maximum amount, i.e., E_c. Therefore, the next state would be $i - E_c + 0$, which should be greater than or equal to 2 to avoid going to the *out of energy* state. Then we can write $i \geq E_c + 2$. The minimum jump occurs when $E_c = 1$ since $E_c \geq 0$. This means the minimum number of states is 3. Comparing this with $s = D + 1$, the minimum energy storage capacity to avoid going to *out of energy* state would be $\min(3, D+1)$. Typically $D+1$ is larger than 3; therefore, the minimum storage to avoid going to either the *full* or *out of energy* states is $C = D$.

VI. Heuristic Schemes

Running an MDP solver, especially when the number of states grows, is too compute-intensive for nanonodes. Although the solution for MDP is a stationary solution, which means it can be solved once and used afterwards, in many situations it is better to use lower complexity schemes, e.g., a lightweight heuristic scheme. First, many parameters such as the capacity of nodes and harvesting models can be different even among neighbor nodes. For example, one node may receive more vibration from human movement when it is mounted on a leg than the chest. So, having a stationary solution may not be the best approach. However, it is a compute-intensive task for limited resource nanonodes to compute the optimal scheme based on their specific parameters such as capacity of energy storage, action set, etc. Therefore, it is useful to develop heuristic methods with performance close to the optimal solution. In the following, we describe our heuristic schemes.

TABLE II
SIMULATION PARAMETERS

Scenario	H (pJ/s)	C (pJ)	E_c (% of C)	B_D
1-Energy Usage	variable	20	50	1
2-Energy Storage	0.5	4-20	50	1
3-Effect of Balance	0.5	6-12	100	3
4-Nonlinear Storage	variable	20	50	1

A. Slow Beginning Fast Ending (SBFE)

The slow beginning fast ending (SBFE) method was inspired by the basic schemes. This heuristic method acts conservatively with a low energy level and aggressively with a high energy level. At the first step, the lowest consumption action from set A, i.e $a_{(0,0)}$, is assigned to the first state, and the highest consumption action, i.e., a_{S_A}, is assigned to the last state. Next, if there are more states remaining than the number of actions, we assign actions to states in an ascending order and then assign the highest consumption for the remaining states. Otherwise, we use the highest consumption rate for all states. This heuristic scheme enables adapting a slow increase in consumption (conservative view) to avoid falling to the *out of energy* state while it uses the highest consumption (aggressive view) to utilize the energy as much as possible when it is available.

B. Adaptive

This heuristic scheme tries to select the actions proportional to the state of energy. The higher the level of current energy, an action with higher consumption is selected. If the level of available energy is below the requested energy action, the next lower consumption action is selected. Indeed, the *adaptive* scheme tries to stabilize the state in one of its close states and also not to move to the first or last states. This approach corresponds with the optimal policy solution as described in Section V-E.

For scenarios with *packet balance*B_D, the list of actions that do not provide the requested B_D are filtered out. Note that SBFE does not support the *packet balance* factor because, as it will be shown in simulation results, even the simple form does not perform well.

VII. SIMULATION

In this section, we evaluate the introduced schemes in terms of several metrics. The goal is to show how each scheme performs in maximizing the utilization of harvested energy. MATLAB is used for simulation. The values of the parameters are listed in Table II. In the first scenario, the performance of various schemes in the utilization of energy is evaluated. In the second scenario, the effect of energy storage on the performance of schemes is presented. The third scenario focuses on how efficiently each scheme can satisfy the requested packet balance. Finally, the fourth scenario illustrates the performance of each scheme when nonlinear linear storage is considered (in scenarios 1–3 linear storage is considered). The harvesting rate follows an exponential distribution, except for the last scenario where the lognormal distribution is also evaluated. Nanonodes communicate based on the Rate Division Time-Spread On-Off Keying pulse method [25], where pulses correspond to logical 1 s and silence correspond to logical 0 s. In all scenarios, E_{rx} is equal to 1 pJ and E_{tx} is set to 2 pJ. Similar results were found for setting E_{tx} to 3, 5 and 10 pJ, with corresponding increases in C. The value of C is determined based on the analysis in Section V-F. The results of simulations are for the long-term behavior of the system where no change in performance metrics 1-digit after the decimal exists.

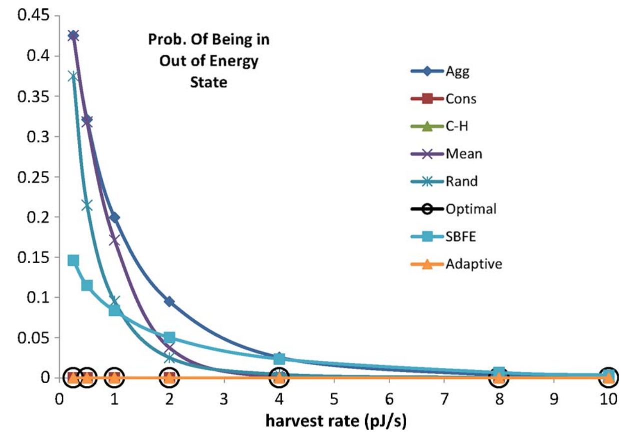

Fig. 2. Probability of being in out of energy state.

A. Energy Usage

We first show how energy is used based on the various schemes. In other words, we want to make sure that we do not consume too aggressively or too conservatively, which will lead to the *out of energy* state or *full energy* state, respectively.

Fig. 2 illustrates the probability of finding a node in the *out of energy* state for each scheme. Clearly, as the harvesting rate is increased with the same consumption rate and energy storage capacity, there is always some energy available. Therefore, the probability of being in *out of energy* goes to zero for all schemes. Not surprisingly, the *optimal* scheme never lets the system be in the *out of energy* state, while the *aggressive* scheme has the highest probability to be in that state. The *optimal*, *adaptive* and *conservative* schemes all have similar performance, almost zero always. The close performance of the *adaptive* scheme to optimal scheme indicates that our lightweight heuristic scheme, *adaptive*, has a near-optimal performance for the probability of being *out of energy* metric. The conservative behavior of the *conservative* scheme results in a situation where there is always some energy left, so the chance of being *out of energy* is zero. *SBFE* performs better than most of other schemes, except *adaptive* and *optimal*. The *random* and *mean* schemes perform roughly near average in comparison to the other schemes.

Fig. 3 illustrates the probability of being in the *full energy* state for various schemes with an increase in harvest rate. As viewed, the behavior is the reverse of the probability of being *out of energy*. As shown in Fig. 3, the probability of being in *full energy state* is increased with an increase in harvesting rare. The *optimal*, *adaptive* and *SBFE* schemes perform better than the basic schemes. Also, note that for the *conservative* and *C-H* schemes, the probability of being in the *full energy* state is

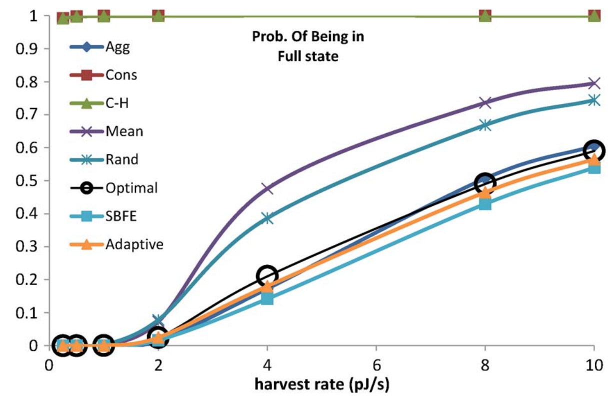

Fig. 3. Probability of being in full energy state.

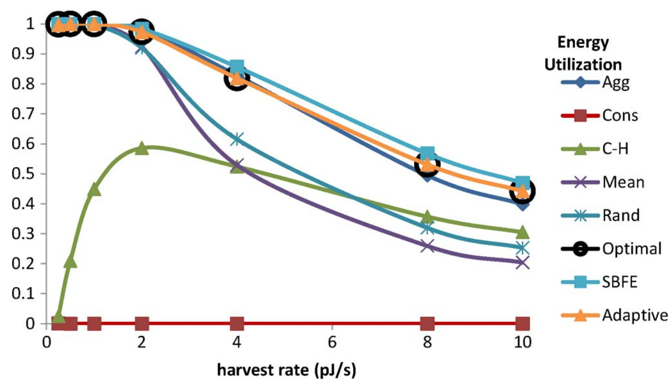

Fig. 4. Energy utilization for various schemes.

almost one, even with a low harvest rate. This occurs because in the long-term, the consumption of energy is low and storage becomes full. After this, since the consumption is very low, the system still stays in the *full energy* state. One may argue that *optimal* and heuristic (*SBFE* and *adaptive*) schemes perform almost similar to the *aggressive* scheme when the harvest rate is increased. First, this happens to avoid going to the *out of energy* state. Second, this phenomena will occur, independent of scheme, due to the high energy harvest rate. In fact, the harvest rate is faster than the consumption rate in this situation, while the energy storage capacity is the same. In practice, the energy storage capacity should be designed in relation to the harvest rate and the maximum usage of energy, as was discussed in Section V-F. In other words, if it is known that the harvest rate would be much higher than consumption, then the storage capacity should be increased to avoid going to the *full energy* state. Again, the *rand* and *mean* schemes perform close to average in comparison with the other schemes.

Fig. 4 represents the performance of the schemes in terms of utilizing the harvested energy. Similar to the convergence of all schemes with the increase of harvest rate for the two previous metrics, here also the *energy utilization* for all schemes comes close to each other. Again as shown in Fig. 4, the very close performance of *optimal*, *adaptive* and *SBFE* surpasses the basic schemes.

A scheme such as *aggressive* has a very similar energy utilization to the *optimal* and *heuristic* schemes when the harvest rate is increased. However, on the other hand, as shown in Fig. 2, this will lead to the *out of energy* state with a higher probability. Note that for smaller harvest rate values, the *optimal* and *heuristic* schemes have almost 100% utilization. Also, as the energy harvest rate is increased, *EU* values converge. Since the energy storage will be full with a high energy harvesting rate and the energy consumption limit is set to the half of energy storage capacity, *EU* values merge towards 0.5.

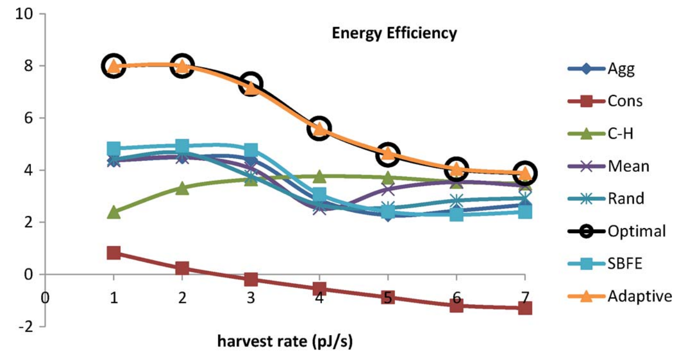

Fig. 5. Energy efficiency for various schemes.

The different behavior of *C-H* (Fig. 4) in comparison to the other schemes is due to the fact that utilization is increased with a higher harvest rate since there is a higher chance of energy arrival. However, after a point, harvest rate = 2 pJ/s, even with the higher arrival of energy, the amount of consumption is limited. Therefore, the utilization falls.

To represent the effect of these three metrics together, the *energy efficiency* (EE) metric is defined as follows

$$EE = \log\left(\frac{EU}{p(o)\cdot p(f)}\right), \quad 0 < p(o), p(f) \le 1, \qquad (4)$$

where $p(o)$ represents the probability of being in the *out of energy* state and $p(f)$ represents the probability of being in the *full energy* state. This shows the efficiency of the schemes for these probabilities and energy utilization. The higher the utilization and the lower the probability of being in the *full* or *out of energy* states, the better. The values of $p(o)$ and $p(f)$ are initially set to a finite small value to avoid division by zero. Fig. 5 shows the energy efficiency for the various schemes. Now it is clear that *optimal* has the highest efficiency for lower harvest rates and outperforms other schemes. The *adaptive* scheme performs similarly to the *optimal* scheme. Of course, as the harvest rate increases, there is always energy, which means that $p(o) \to 0$ and $p(f) \to 1$. Similarly, the *energy utilization* goes down because there is not enough storage to store the energy and utilize it. Therefore, the *energy efficiency* metric goes down, independent of the scheme. The *energy utilization* of the *conservative* scheme is low, therefore an increase in the harvest rate, and correspondingly decrease in *EU*, will result in the taking the log of a small value in (4), which is a negative number. Since the *optimal* and *adaptive* schemes outperform other schemes, for the sake of simplicity, the remaining results are shown only for them.

B. Effect of Energy Storage

As shown in Section V-F, the energy storage capacity is one of the main design parameters in relation to the harvesting rate.

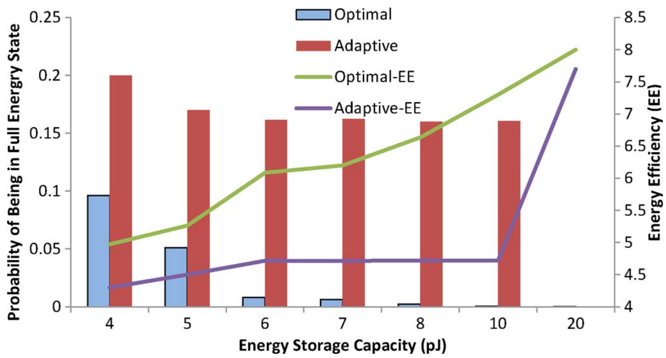

Fig. 6. Probability of being in full energy state and energy efficiency with change of capacity.

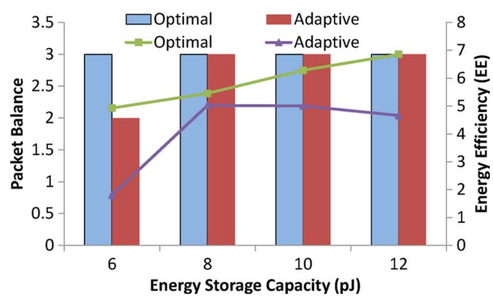

Fig. 7. Packet balance and energy efficiency with change of storage capacity. the target packet balance B_D was 3.

Fig. 6 illustrates the probability of being in the *full energy* state with the increase of storage capacity. Clearly, as the storage capacity is increased, the chance of being in the *full energy* state is reduced due to there being more capacity available. The probability of being in the *full energy* for the *optimal* scheme goes close to zero at storage capacity 6 pJ. This confirms the analysis in Section V-F, with setting $C = D$ and $\delta = 10^{-6}$ in (1).

Fig. 6 also shows the energy efficiency of the schemes with the change of storage capacity. As can be seen, the *energy efficiency* between the *optimal* and *adaptive* schemes becomes closer as the energy capacity is increased. This behavior shows that as the energy storage becomes larger, providing the energy utilization is simpler. However, limited energy storage plays an important role for limited energy storage for nanonodes.

C. Effect of Balance

Here, we evaluate the performance of the schemes in satisfying the *packet balance* factor. We set B_D to 3, which means the number of receptions has to be 3× the number of transmissions. In general, as shown in Fig. 7, the *adaptive* scheme performs close to the *optimal* scheme for balancing receptions and transmissions. The performance of *optimal* in meeting the balance factor degrades only when the storage capacity becomes smaller. In this case, as illustrated in Fig. 7, the *optimal* scheme would have a higher energy efficiency. Similar results were found for packet balances 5 and 7.

D. Nonlinear Storage

In this experiment, we evaluate the effect of nonlinear energy storage on *energy efficiency*. We assume that nonlinear storage

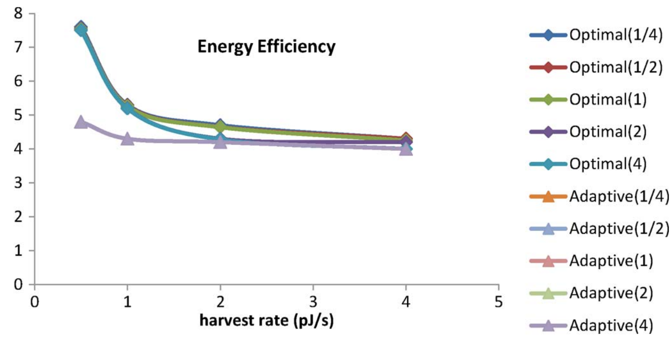

Fig. 8. Energy efficiency for linear and nonlinear storage—exponential harvesting.

will follow a polynomial of degree d in form of $y = x^d$. Fig. 8 represents the effect of nonlinear storage on energy efficiency when the storage has nonlinear structure with degrees 1/4, 1/2, 2, and 4. In general, for the *optimal* scheme the lower the degree, the higher the energy efficiency. This shows that the *optimal* scheme takes into account the storage effect, especially when the energy harvesting has a lower rate, here the lower degree. The *adaptive* scheme has the same performance independent of the storage model since storage is not included in the scheme.

Similar behavior was observed for harvesting with a log-normal distribution. The comparison of these two harvesting distribution models illustrates that the effect of the harvesting distribution is less than the energy storage model.

VIII. Conclusion

In this paper, we introduced the problem of optimum energy consumption for nanonodes that harvest energy from stochastic resources. Nanoscale properties affect the harvesting and storing of energy. Particularly, the low rate of energy harvesting and limited energy storage capacity makes the problem of energy consumption optimization difficult. We analyzed the problem of finding the optimum consumption of harvested energy for nanonodes and proposed an optimal solution that not only maximizes the utilization, but also satisfies the ratio of packet receptions to transmissions. We showed through simulation that a light-weight heuristic approach that attempts to match consumption with current energy state has near optimal performance.

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