Energy Allocation Algorithm for Energy Harvesting Wireless Sensor Network

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Abstract: the life-time of wireless sensor network can easily be prolonged very significantly, with the use of energy harvesting technologies. The energy management policy of an energy harvesting WSN take into account the energy replenishment process, unlike a traditional WSN powered by non-rechargeable batteries. In this paper, we present a study about the energy allocation for transmission and sensing in an energy harvesting sensor node with a finite buffer and rechargeable battery. The aim of the sensor node is to maximize the total data transmitted in a finite horizon subject to channel fading, energy harvesting rate and energy availability in the battery. Here in this paper we present a energy distribution algorithm using dynamic programming for energy allocation problem. We conduct simulations to compare the performance between our proposed algorithm and the existing algorithm from[1]. Simulation results show that the proposed algorithm achieves a higher throughput than the existing algorithm under different settings.

Index Terms—Energy harvesting,Markov decision process(MDP),resource allocation, wireless sensor network(WSN)

i) INTRODUCTION

A wireless sensor network (WSN) is composed of a large number of sensor nodes that are deployed for various purposes such as environmental sensing, monitoring, and maintenance. A sensor node is powered by a non-rechargeable battery, having a finite energy storage capacity. so, a wireless sensor network can only function for a finite amount of time. Various research work have been carried out to prolong the lifetime of a WSN by enhancing its energy efficiency [2]–[5].

Alternatively, the idea of energy harvesting was proposed to address the problem of finite lifetime in a WSN by enabling the wireless sensor nodes to replenish energy from ambient sources, such as solar, wind, and vibrations [6], [7]. The design issues of an energy harvesting WSN are different from a non-rechargeable battery operated WSN in various ways. As there is unlimited energy available to the sensor nodes, an energy harvesting WSN can remain operated for a long period of time. Hence,to conserve energy is not our primarily design issue in energy harvesting WSN. Second, the energy management strategy for an energy harvesting WSN needs to take into account the energy replenishment process. Third, the energy availability constraint, which requires the energy consumption to be less than the energy stored in the battery,must be met at all time. This constraint complicates the design of an energy management algorithm, since the outcome in the future would affected by current energy consumption decision. Some of the recent works on energy harvesting WSNs have formulated the energy management problem as a dynamic programming (DP) [8], [9] problem. Ho et al. in [1] proposed a throughput-optimal energy allocation algorithm for a time- slotted system under time-varying fading channel and energy source by using dynamic programming. A throughput-optimal energy allocation policy[10] was derived in a continuous time model and some suboptimal online waterfilling schemes were proposed to address the dimensionality problem inherent in the DP solution. Chen et al. in [11] studied the energy allocation problem of a single node using the shortest path approach. A simple distributed heuristic scheme was proposed that solved the joint energy allocation and routing problem in a rechargeable WSN. Sharma et al. in [12] proposed some energy management schemes for a single energy harvesting sensor node that achieved the maximum throughput and minimum mean de- lay. Gatzianas et al. in [13] presented an online adaptive transmission scheme for wireless networks with rechargeable batteries that maximizes total system utility and stabilizes the data queue using Lyapunov techniques. In [14], utility-optimal energy allocation algorithms were proposed for systems with predictable or stochastic energy availability.

Most of these results from [1], [10]–[14] assumed either an infinitely long data backlog or data buffer. Yet, it is more reasonable if a finite data buffer is considered. Besides, the energy consumed in data sensing has always been overlooked in the literature. This motivates us to design an energy distribution algorithm for energy harvesting WSNs which takes into account both the data sensing energy consumption and the finite capacity of the data buffer. The results show that the our proposed algorithm achieves a higher throughput than the existing algorithm under various settings. Here i study the impact of data-sensing efficiency (i.e., the amount of data that the sensor can sense per unit energy) on the performance of total data transmitted. Unlike the various existing works in the literature [1], [10]–[14], we take into account a finite data buffer and the energy consumed for sensing.

Kansal et al. [15] proposed analytically tractable models to characterize the complex time-varying nature of en- ergy sources. Distributed algorithms were developed to utilize the harvested energy efficiently. Srivastava and Koksal [16] analyzed the limits of the performance of energy harvesting sensor nodes with finite data and energy storage. An energy management scheme was proposed that achieves the optimal utility asymptotically. Mao et al. [17] studied the joint databuffer and rechargeable battery control problem that aims to maximize the long-term average sensing rate of a wireless sensor network. , power allocation, routing algorithms and joint rate control were proposed for both single-hop and multihop networks. Khouzani et al. [18] proposed routing and scheduling policies that do not require explicit knowledge of the statistics of the energy replenishment or the traffic generation processes. They were able to learn and adapt to time variations in the physical and network environments dynamically, to achieve the long-term optimal data rates. In [19], energy management policies were identified that guarantees a minimum average distortion while ensuring the stability of the data buffer.Wang and Liu [20] considered the near-optimal power control policies with a saturated data queue in both the finite-horizon and infinite-horizon cases.

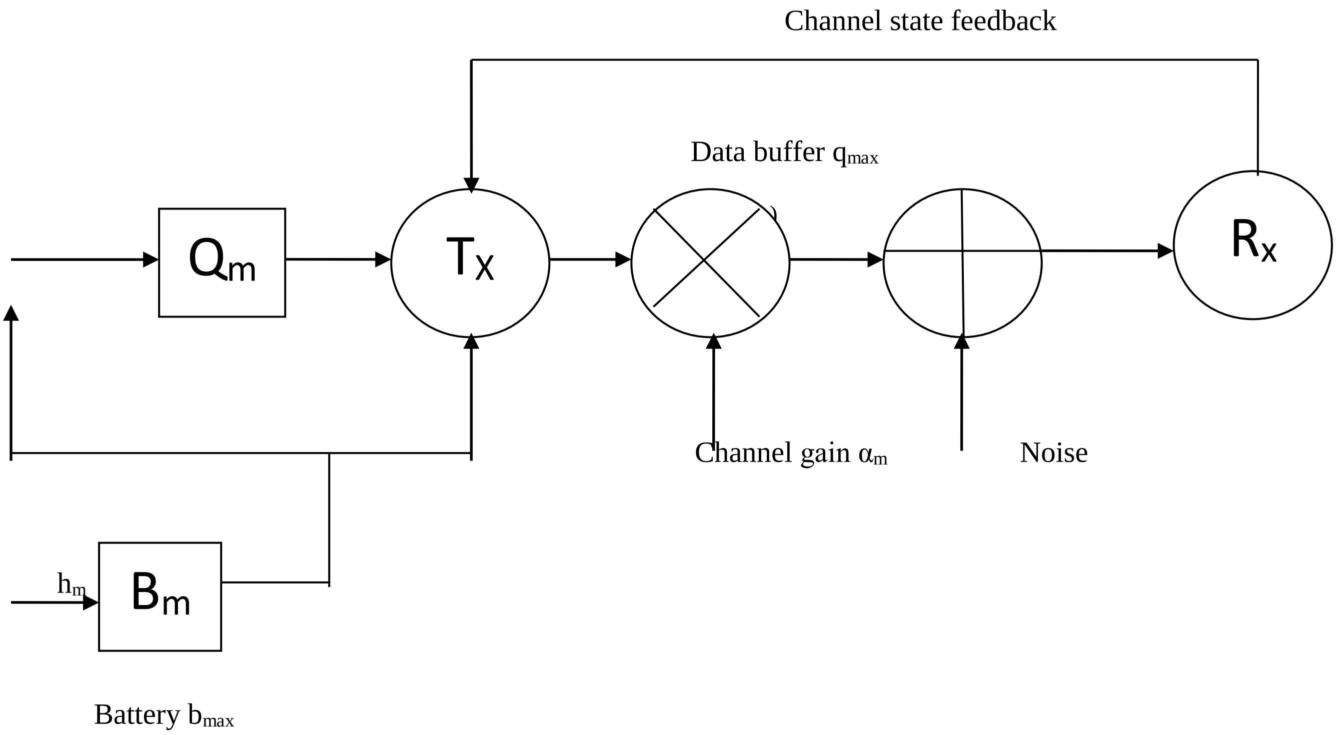


Fig. 1. System model of an energy harvesting wireless sensor node transmit- ting data to the receiver Rx of the sink. At allocation interval m, the random variables are the energy to be harvested h_m and the channel gain α_m. Due to channel feedback delay and the time required to track the energy harvesting rate, we assume that the values of α_m-1 and h_m-1 are only known at the beginning of allocation interval m. The optimization variables (or actions) are the energy consumed for transmission ek and sensing s_m. The stored battery level is b_m and the amount of data available in the buffer is q_m. $x(s_m)$ is the amount of data obtained by using sk amount of energy. The amount of data transmitted in allocation interval m is $\min\{\mu(e_m,\alpha_m),q_m\}$. Our problem is to optimally allocate e_m and s_m such that the expected total amount of data transmitted until the sensor node stops functioning is maximized.[1]

II) SYSTEM MODEL

As shown in Fig. 1, we assume a single energy harvesting sensor node, which contains a rechargeable battery with capacity bmax Joule and a data buffer with size qmax Mbits. We assume that the system is time-slotted with M time slots and the duration of a time slot is K sec. Let m ∈M {0,1,...,M−1} be the index of time slot. The sensor node performs sensing in the field, stores the sensed data in the buffer, and transmits the data to the receiver Rx of the sink over a wireless channel. We consider an additive white Gaussian noise (AWGN) channel with block flat fading. Then the channel will be constant for the duration of each time slot, but may change at the slot boundaries. Let α_m be the channel gain in time slot m. We assume that the sink sends delayed channel state infor- mation (CSI) of the previous time slot back to the sensor node. In other words, at the beginning of time slot m, the sensor node only knows the value of α_{m-1}, but not α_m. At the beginning of time slot m, the stored battery level is b_m and the amount of stored data in the data buffer is q_m. During the whole time slot m, the sensor node is able to replenish energy by h_m, which can be used for sensing or transmission in time slot m +1 onward. As a result, the sensor node does not know the value of h_m until the next time slot m +1. In other words, at the beginning of time slot m, the sensor node knows the value of h_{m-1}, but not h_m. If the channel gain is α_m and the allocated transmission energy is e_m in time slot m, so the instantaneous power of transmission is e_m D , and the sensor node is able to transmit $\mu(e_m,\alpha_m)$ bits of data in time slot m. so $\mu(e_m,\alpha_m)$ is a monotonically non-decreasing and concave function in e_m given α_m. One such function is given by [21]:

$\mu(e_m,\alpha_m)$=DW $\log_2 1+ \alpha_m e_m$ N_0WD bits (1)

where N_0 is the power spectral density of the Gaussian noise, and W is the bandwidth of the channel. For sensing in time slot m, we letx(s_m) be the amount of data generated when s_m units of energy are used for sensing. In general, x(s_m) is a monotonically non-decreasing and concave function in s_m.

Fig.[2] Timing diagram of an MDP[2]

The data obtained by sensing in time slot m will be stored in the data buffer until it is transmitted in the following time slots. Except for sensing and transmission, we assume that other circuits in the such that the overall expected throughput in the M time slots is maximized. To achieve this goal, it has to maintain a good tradeoff between the energy allocation for e_m and s_m. Given a fixed energy budget in a time slot, if e_m is too small, then the throughput in mth time slot will be small. However If e_m is too large, then s_m will be small that insufficient amount of sensing data is stored in the buffer for transmission in the next time slot, which leads to a reduction in throughput. In addition, the total energy budget $e_m + s_m$ in time slot m should also be carefully controlled. If the energy management policy is highly aggressive such that the rate of energy harvesting is lesser than the rate of energy consumption, it may produce an energy outage, which prevents the proper functioning of sensor node. On the other hand, an overly conservative energy management policy would limit the throughput in each time slot. Thus it is a challenging problem to decide the values of e_m and s_m optimally in each time slot m ∈M.

III) PROBLEM FORMULATION

In this section, we formulate the problem of finding the optimal energy allocation for sensing and transmission as a finite-horizon sequential decision problem [8], [9], which consists of five sensor node consume negligible energy. The sensor node needs to decide on e_m and s_m, for all m ∈M

elements:, states, actions, state transition probabilities, decision epochs and rewards. The decision epochs are

$m \in M= \{0,1,...,M-1\}$. (2)

At the beginning of time slot m, the state of the system is denoted as

$Y_m =(b_m,q_m,h_{m-1},\alpha_{m-1})$, (3)

which includes the battery energy state b_m and data buffer state q_m for the current time slot m, as well as the energy harvesting state h_{m-1} and channel state α_{m-1} in the previous m-1 time slot. If the energy state of battery in m time slot , the sensor node harvests energy h_m units from the environment. On the other hand, it consumes e_m units of energy for data transmission and s_m units of energy for sensing. Since the battery has a finite capacity b_{max}, hence the energy stored in the battery is given as

$b_{m+1} = \min\{b_m - (e_m + s_m)+h_m,bmax\},\forall m \in M$. ……………………………. (4)

It ensures that the maximum stored energy bmax is not exceeded. We assume that the initial energy b_0 is known and satisfies the constraint that $0 \le b_0 \le$ bmax. Moreover, the amount of energy consumed for sensing and transmission must be no more than the battery level:

$e_m + s_m \leq b_m, \forall m \in M$. (5)

Second, for the data buffer state in time slot m, $x(s_m)$ amount of sensing data are generated and queued up in the data buffer if s_m units of energy are allocated for sensing. On the other hand, $\mu(e_m,\alpha_m)$ amount of data are transmitted and removed from the data buffer if e_m units of energy are used for transmission. However, since the data available in the data buffer for transmission at time slot m is q_m, the throughput at time slot m is given by $\min\{\mu(e_m,\alpha_m),q_m\}$. Since the data buffer is finite with capacity qmax, the amount of data in the buffer is then updated as:

$q_{m+1}=\min\{[q_m-\mu(e_m,\alpha_m)]+ x(s_m),q_{max}\},\forall m \in M$, …………. (6)

with [z]+ = max[z,0]. We assume that the initial amount of data in the data buffer q0 is known and satisfies $0 \leq q0 \leq qmax$. Equation (6) implies that if the energy allocated by the sensor is high for transmission so that $\mu(e_m,\alpha_m) > q_m$, then energy is properly utilized. On the other hand, if the sensor allocates too much energy for sensing so that $x(s_m) > qmax$, then the data buffer overflow and energy is wasted in network. So the sensor should make a proper energy allocation decision at each time slot. Third, since the energy harvesting rate and the current channel state information at time slot m is not known to the sensor, hence we use two first order independent stationary Markovian models to model h_k and α_k. The random variable h_m takes values in some finite set $H = \{H_1,H_2,...,H_N\}$. On the other hand the random variable α_m takes values in some finite set $A = \{A_1,A_2,...,A_M\}$. The transition probability of these two independent random variables are denoted as $P(h_m | h_{m-1})$ and $P(\alpha_m | \alpha_{m-1})$. Based on the current state y_m at time slot m, the sensor will choose to consume e_m units of energy for data transmission and s_m units of energy for sensing. That is, an action (e_m,s_m) is taken for transmission and sensing energy allocation from its feasible set $U_m(y_m)$. We have

$(e_m,s_m) \in U_m(y_m)=\{(e_m,s_m)|e_m + s_m \leq b_m,e_m\geq 0,s_m\geq 0\}$, ……………………..(7)

where $U_m(y_m)$ represents the feasible set of (e_m,s_m) at time slot m. The constraint $e_m + s_m \leq b_m$, $\forall m \in M$ ensures that the amount of energy consumed for sensing and transmission must be no more than the battery level. In addition, it is possible to impose some additional constraints on (e_m,s_m).As for example, a constraint on the minimum amount of energy for sensing or transmission to ensure a minimum amount of sensed data or transmitted data for each time slot, respectively. Also, the maximum transmission power constraint can be imposed. The state transition probability

$P(y_{m+1} | y_m,e_m,s_m)$ is the probability at time slot m when the system will go into state y_{m+1} if action (e_m,s_m) is taken at state y_m. So due to the independence between (b_{m+1},h_m) and (q_{m+1},α_m) for all $m \in M$, the state transition probability is..

$P(y_{m+1} | y_m,e_m,s_m)$

$= P(b_{m+1},q_{m+1},h_m,\alpha_m | b_m,q_m,h_{m-1},\alpha_{m-1},e_m,s_m)$

$= P(b_{m+1},h_m | b_m,h_{m-1},e_m,s_m)P(q_{m+1},\alpha_m | q_m,\alpha_{m-1},e_m,s_m)$

$= P(b_{m+1} | b_m,h_m,e_m,s_m)P(h_m | h_{m-1})$

$\times P(q_{m+1} | q_m,\alpha_m,e_m,s_m)P(\alpha_m | \alpha_{m-1})$, …………………………….(8)

where

$P(b_{m+1} | b_m,h_m,e_m,s_m) = 1$,

if (4) is satisfied,

0, otherwise, ……………………………..(9)

$P(q_{m+1} | q_m,\alpha_m,e_m,s_m) = 1$,

if (6) is satisfied,

0, otherwise. ……………………………(10)

$P(h_m \mid h_{m-1})$ and $P(\alpha_m \mid \alpha_{m-1})$ are defined corresponding to Markov model.

Given the current state y_k and the action (e_m,s_m), $E\alpha_m[\mu(e_m,\alpha_m)]$ is the expected amount of data that can be transmitted when e_m units of energy are used for transmission. As the data available in the data buffer for transmission at time slot m is q_m, the expected throughput (i.e., the amount of data transmitted in the time slot) at time slot m is given by $E\alpha_m[\min\{\mu(e_m,\alpha_m),q_m\}]$. We define the expected reward at time slot m to be the expected throughput is..

$E\alpha_m[\min\{\mu(e_m,\alpha_m),q_m\}]$

$= \min \alpha\in A\mu(e_m,\alpha)P(\alpha|\alpha_{m-1}),q_m$…. (11)

Let $\pi = \{(e_m(y_m),s_m(y_m)),\forall\ y_m,m \in M\}$be the power allocation policy, where$(e_m(y_m),s_m(y_m))$ is the transmissionand sensing power allocation at state y_m under policy π.A feasible policy should satisfy (7) in all the time slots. Let Π be the feasible set of π. Since α_m and h_m are random variables, the sensor node aims to find an optimal and feasible sensing and transmit power allocation policy $\pi*$ that maximizes the total expected reward, i.e., the total expected throughput summed over a finite horizon of K time slots. That is, given the initial state $y_0 =(b_0,q_0,h-1,\alpha-1)$ in the first time slot, it aims to solve the following optimization problem

$T * = \max \pi\in\Pi M-1 m=0E\min\{q_m,\mu(e_m,\alpha_m)\}y0,\pi,$ (12)

where $E[\cdot]$ denotes the statistical expectation taken over all relevant random variables given initial state y_0 and policy π. In general, the optimization problem in (12) cannot be solved independently for each time slot due to the causality constraints on different variables. For example, the current energy consumption affects the energy availability in the next time slot, and thus affects the future energy allocation. Also, the energy allocated for sensing at the current time slot affects the amount of data in the queue for transmission in the next time slot. For such sequential optimization problem (12) under channel condition and energy harvesting rate uncertainties, we can solve it optimally using finite-horizon DP.

IV)DYNAMIC PROGRAMMING FOR ENERGY ALLOCATION

In this section, by using finite- horizon DP i solve problem (12). Here I proposed an algorithm to achieves the maximal expected throughput in problem (12). Let $J_m(b_m,q_m,h_{m-1},\alpha_{m-1})$ be the maximum expected throughput from time slot m to m −1, given that the system is in state $(b_m,q_m,h_{m-1},\alpha_{m-1})$ at time slot m immediately before the decision. The following recursive equations starting from m = M − 1 to m =0 given by the bellman's equations..

For m = M − 1, we have

$J_{m-1}(b_{m-1},q_{m-1},h_{m-2},\alpha_{m-2})$

$= \max\ (e_{m-1},s_{m-1}) \in U_{m-1}(y_{m-1})E_{\alpha m-1}[\min\{\mu(e_{m-1},\alpha_{m-1}),q_{m-1}\}|\alpha_{m-2}]$……..(13(i))

For m = M − 2,...,0, we have

$J_m(b_m,q_m,h_{m-1},\alpha_{m-1})$

$=\max_{(em,sm)\in Um(ym)}E\alpha_m[\min\{\mu(e_m,\alpha_m),q_m\}|\alpha_{m-1}]$ ……………………. (13(ii))

$+ E_{hm,\alpha m}[J_{m+1}(b_{m+1},q_{m+1},h_m,\alpha_m)|h_{m-1},\alpha_{m-1}],$

where b_{m+1} and q_{m+1} are updated as in (4) and (6), respectively. Notice that if the feasible set of (e_m,s_m) is $U_m(y_m)$ as defined in (7), then (13a) can be simplified as

$J_{M-1}(b_{m-1},q_{m-1},h_{m-2},\alpha_{m-2})$

$=E_{\alpha m-1}[\min\{\mu(b_{m-1},\alpha_{m-1}),q_{m-1}\}|\alpha_{m-2}]$.

…………………………(14)

That is, we use all the available energy for transmission in the final time slot. Thus the optimal energy allocation for the final time slot is $(e*_{m-1},s*_{m-1})=(b_{M-1},0)$. For (13(ii)), ,the expected immediate throughput for time slot k and the expected total future throughput respectively for time slot m +1to m − 1 if action (e_m,s_m) is chosen. so the equation (13b) describes the tradeoff between the current and the future rewards.

V) PERFORMANCE EVALUATION

In this section, we evaluate the performance of our proposed algorithm by comparing its achieved throughput with that of the existing algorithm from [1]. Assuming a band-limited channel having a channel bandwidth W = 100 KHz and the noise power spectral density is N_0 = 10 −18 W/Hz. The channel state can be "g = good", "n = normal", or "b = bad". It evolves according to the three-state Markov chain with the transition matrix of the Markov chain given by

$$P_G = \begin{bmatrix} Pbb & Pbn & Pbg \\ Pnb & Pnn & Png \\ Pgb & Pgn & Pgg \end{bmatrix} = \begin{bmatrix} .3 & .7 & 0 \\ .25 & .5 & .25 \\ 0 & .7 & .3 \end{bmatrix} \quad \ldots\ldots\ldots\ldots(15)$$

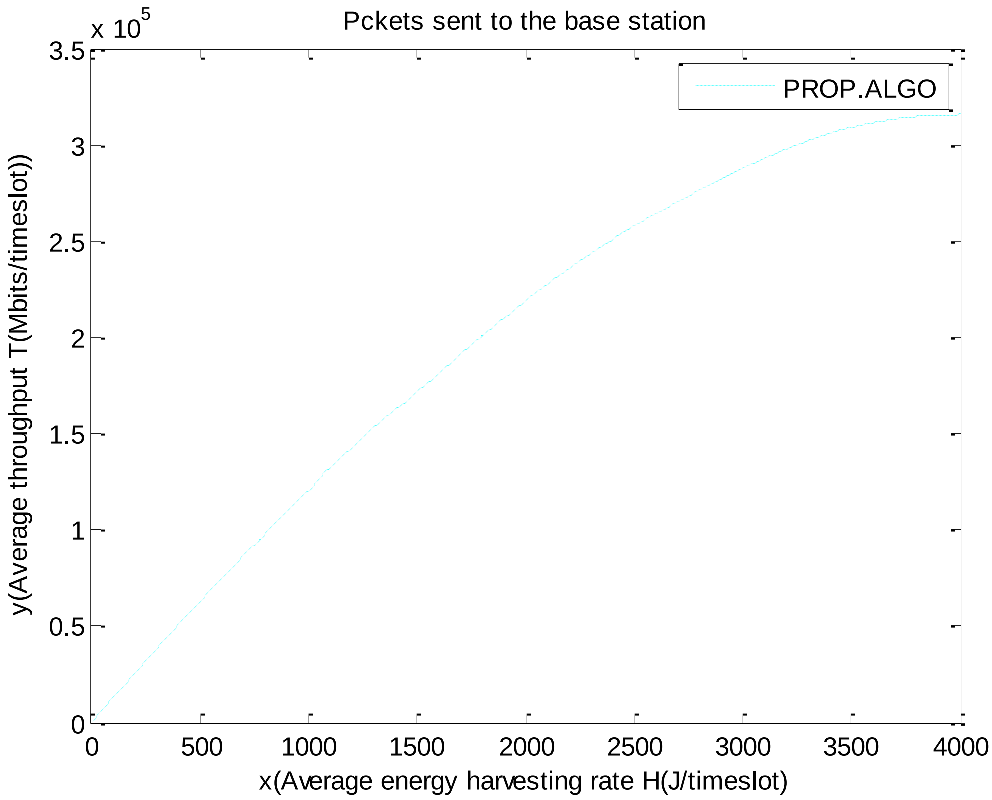
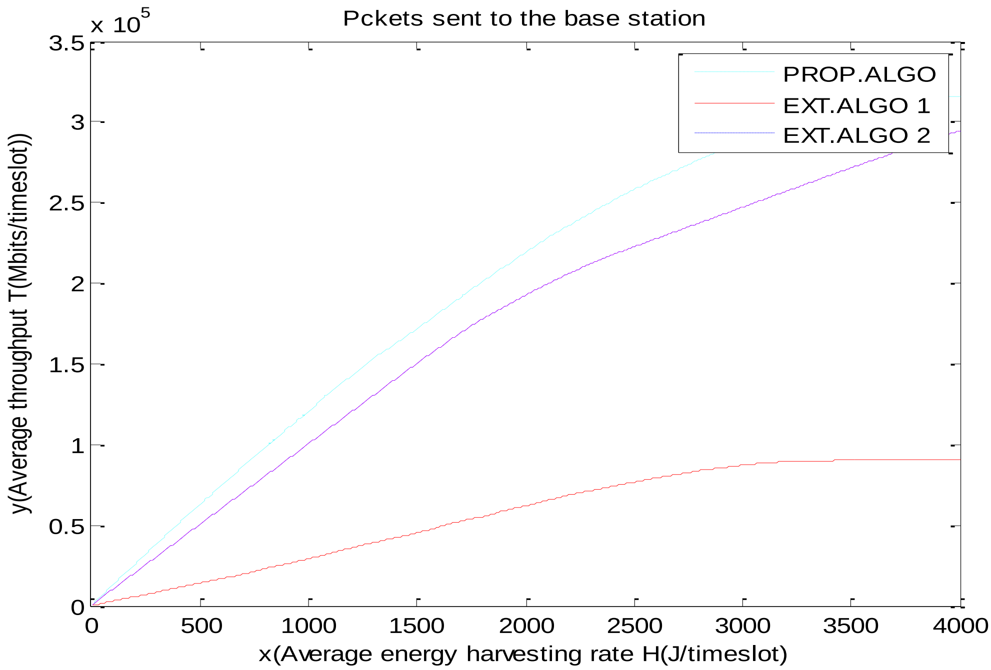


Fig.[3]

where P_{AB} represents the probability of the channel state going from state A to state B , where A and B ∈{g,n,b}. The gain of the channel G is defined as 1.5 × 10^{-13}, 1 × $10^{-13,}$ and 0.5 × 10^{-13} when the channel state is "Good", "Normal", and "Bad", respectively. The buffer size of battery,b_{max} is consider to be 100 Joules, and the data buffer size , qmax is consider to be as 1 Mbits. For tractability, we assume that the energy harvesting state e_m takes values from the finite set E = [E_1,E_2,E_3,E_4] and according to the four-state Markov chain with the state transition probability given by

$$P_h = \begin{bmatrix} .3 & .7 & 0 & 0 \\ .25 & .5 & .25 & 0 \\ 0 & .25 & .5 & .25 \\ 0 & 0 & .7 & .3 \end{bmatrix} \quad \ldots\ldots\ldots(16)$$



Fig[4]

where P_{EiEj} represents the probability of the energy harvesting state going from state E_i to state E_j, $\forall$ i, j $\in$ {1,2,3,4}. The probability of steady state is then given by [P_{E1} P_{E2} P_{E3} P_{E4}] = [0 .13 0.37 0.37 0.13].

$x(s_m)$ is assumed to be a linear function and given by

$x(s_m)=\gamma s_m$, ………….. (17)

where γ is the parameter fordata-sensing efficiency. Where i denote the average throughput as H' ,hence given by

– $H' = \frac{H*}{M}$, …………… (18)

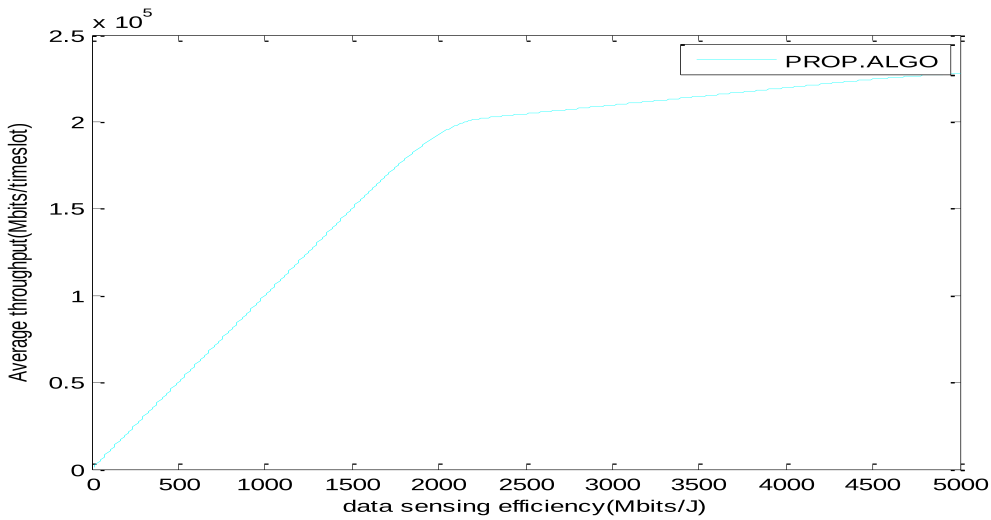


Fig.[5]

where H ∗ is the maximal total expected throughput over K time slots defined in (12). Algorithm in [1] neglected the sensing energy and assumed infinite backlogged data. For comparison purpose, we modify the proposed algorithm with size q_{max} . We assume that the sensor allocates a fixed percentage of energy available in the battery for sensing in each time slot, and optimizes the energy allocated for transmission. By examining the average throughput H of the existing algorithm with different number of total time slots M. The efficiency parameter of data-sensing γ is set to be 0.02 Mbits/J.So in the existing algorithm We set the fixed percentage of energy for sensing. The value of energy harvesting rate is taken from the set E = {E_1,E_2,E_3,E_4} = {6,12,18,24} J/time slot. our proposed algorithm achieves 32% higher average throughput than the existing algorithm when M = 30. The reason is that in the existing algorithm, the sensor just controls the transmission energy . However, in our proposed algorithm, the sensing energy and transmitting energy both is allocated optimally, in turn which gives us a better performance than the previous algorithm.

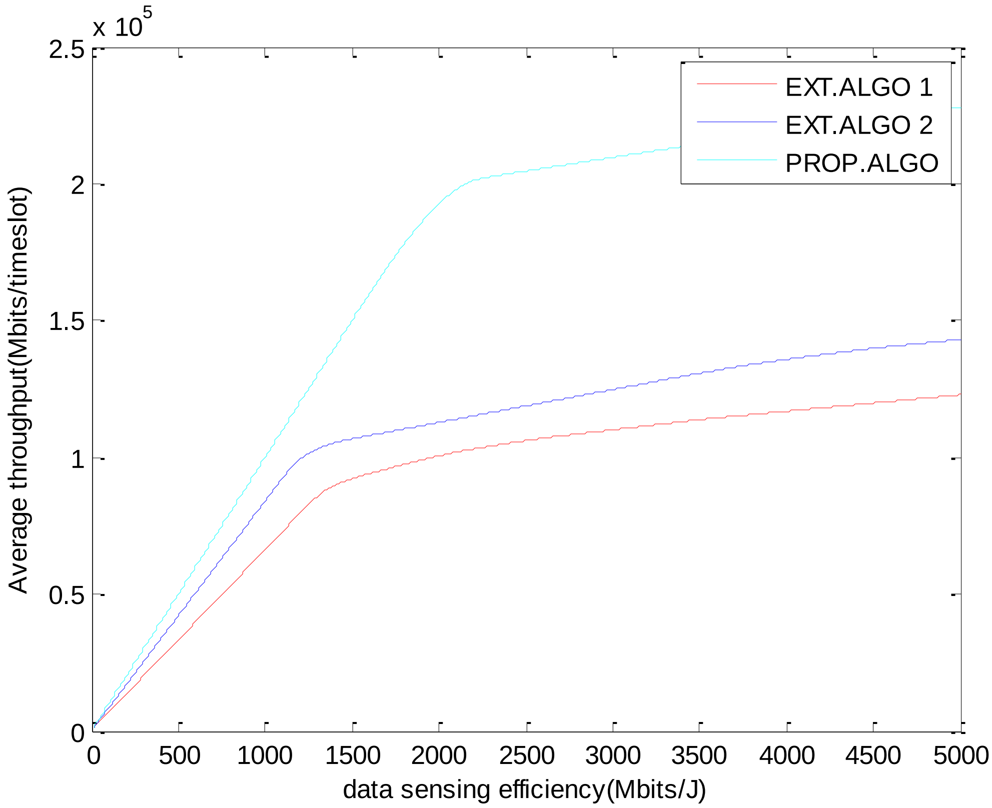


Fig.[6]

we consider the performance of the two algorithms under different average energy harvesting rates. Here we plot the average throughput versus the average energy harvesting rate. However if E is high we observe that our proposed algorithm performs much better than the existing algorithm. As shown in Fig. 3 & 4, our proposed algorithm achieves 105% higher average throughput than the existing algorithm when the average energy harvesting rate $\bar{E}$ = 35J/time slot. Moreover, as the harvested energy cannot be accommodated the throughput of the existing algorithm saturates very quickly as the average harvesting rate is increased.But in our proposed algorithm, energy wastage will not occur as long as the data buffer is large enough and harvesting rate is less than b_{max}. The reason for the better performance is that under the proposed algorithm, the sensor node maintains a good balance between the energy allocated for sensing and transmission.

Finally, we study the average throughput under different value of γ. since the sensor node spends less energy for sensing the same amount of data, A larger value of γ corresponds to a higher data sensing efficiency,as shoen in fig. 5 & 6 when γ is increased.because more energy is available for data transmission the throughput increases as well.However the performance saturates as γ is increased beyond a limited value. When γ approaches infinite, it corresponds to the case where sensing is highly efficient.

VI) CONCLUSIONS

Here, i studied the problem of maximizing the total amount of data transmitted under channel fluctuations and energy harvesting rate variations in a time-slotted system for an energy harvesting sensor node. First time the energy consumed and a finite data buffer for sensing data was considered. Sensor should achieve a good tradeoff between the energy consumed for transmission and sensing. Here i discussed the problem as an infinite-horizon markov decision process. I obtained the new policy and proposed an new algorithm based on value iterations in the MDP. So i assume that there was infinite data back-log we studied the transmission energy allocation problem. I proved that the existing policy was a monotonically increasing function of the available battery energy and obtained structural results for the existing policy. Finally, simulate the results to compare the performances of our proposed algorithm with the previous existing algorithms. We also studied that how the total amount of data transmitted depends on the average energy harvesting rate, the data sensing efficiency and various other parameters. The outcome showed that this algorithm transmitted the largest amount of data among the three algorithms. Future work is the extension of our model to a multihop setting for data transmission.

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