Lifetime and Buffer-Size Optimization for RF Powered Wireless Sensor Networks

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Abstract: Radio Frequency-Energy Harvesting (RF-EH) system usually incorporates ‘harvest-store-use’ mechanism, i.e. the harvested RF energy is first stored in an energy buffer and when the stored energy level is sufficient enough to power an application it is then supplied to the device. To improve the network’s performance in terms of lifetime and buffer capacity, it is crucial to develop a model for RF powered Wireless Sensor Networks (WSNs), which considers source-load relations, buffer size and ambient conditions within the context of Energy Neutral Operation (ENO) and minimum energy wastage. In this paper, we propose a model for RF powered WSNs that makes use of available RF energy with variations in maximum and minimum energy levels for two different worst case scenarios encompassing ENO and buffer requirements. We develop an algorithm based on the proposed model to find the optimum energy consumption rate of each sensor nodes that would ensure maximum lifetime of the WSN with minimum buffer capacity. We verified our approach by comparing the results with all other possible consumption rates. We also performed a comparative analysis to find the effect of available RF energy fluctuation in the individual sensor nodes’ lifetime.

1 INTRODUCTION

Radio Frequency Energy Harvesting (RF-EH) technique is a promising technique to sustainably power Wireless Sensor Networks (WSNs) by harvesting energy from ambient RF signals. This technique has added benefits of being wireless, energy is available in the form of transmitted energy from RF sources, small size and low cost when compared to energy harvesting systems from other sources (Lu et al., 2015a). However, RF energy harvesting as a new element in WSNs also introduces challenges for developing efficient energy management system along with other design issues like data delivery scheme, topology, connectivity and energy storage technology (Lu et al., 2015b, Zahid Kausar et al., 2014).

For any EH system, to optimize energy utility and to minimize waste, the system needs to operate in accordance with the energy profile of the source and also its design should consider load and harvester properties (Pimentel and Musilek, 2010) . Energy neutrality is a condition for an EH system to operate perpetually, i.e., for Energy Neutral Operation (ENO), the energy used by a system should always be less than the energy harvested, which can be ensured by incorporating an energy management system between the harvester and the load to satisfy the energy generation profile from the energy consumption profile (Zahid Kausar et al., 2014, Morsi et al., 2015).

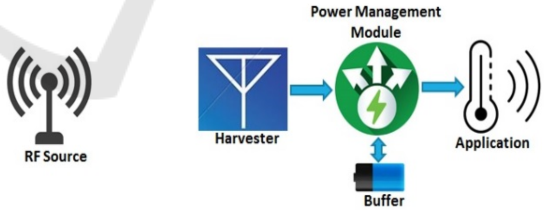

Figure 1: Block diagram of a RF-EH System.

The energy management system can adopt two methods to control the incoming energy flow, i.e., *harvest-use* or *harvest-store-use*. In *harvest-use* method, the harvested energy is immediately used to power the application, for this, the converted electricity has to constantly exceed the minimum energy required by the application. In the *harvest-store-use* method, the network node has an energy storage buffer, a rechargeable battery or a capacitor, to store the converted electricity. Whenever the harvested energy is more than load’s consumption,

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the excess energy is stored in the buffer for future use (Lu et al., 2015b).

To determine the load energy consumption rate for various associated source energy levels, it is necessary to develop a model for RF powered WSNs, which would ensure continuous work of applications with minimal energy wastage even in worst case scenarios and it should also be applicable for diverse ambient conditions. In addition, the relation between harvested energy, consumed energy and energy buffer size defined by the model, should be able to represent the network's optimal performance scenario (Kansal et al., 2007).

Network lifetime is one of the crucial performance matrices for a WSN, which can be prolonged by improving its energy efficiency. Moreover, the location and orientation of sensor nodes affect their energy harvesting rates, which eventually determines the lifetime of each individual node. Understanding the relation between the node's energy harvesting rate and lifetime, within the periphery of energy neutrality and zero energy wastage, is important for designing any energy-aware routing algorithm (Cammarano et al., 2016, Mansourkiaie et al., 2017).

In this paper, we present a system model for RF powered WSN based on *harvest-store-use* method that takes into consideration the worst case scenarios. The model provides optimum values of load energy consumption rate and buffer size for a given energy harvesting rate, increasing the WSN's lifetime. In particular, we make the following contributions:

- We propose a model for RF powered WSN incorporating harvester's efficiency and ambient conditions, which ensures energy neutrality and minimal energy wastage.
- We develop an algorithm based on the proposed model that selects the optimum value for load energy consumption rate and buffer capacity from all valid set of values.
- We analyse the lifetime and buffer capacity of the WSN for optimum load energy consumption rate along with all other non-optimum values.
- We also analyse and compare the maximum and minimum lifetimes of sensor nodes with optimal energy consumption rate exposed to various RF energy fluctuation levels.

The rest of the paper is organized as follows. Section 2 presents related works in the area of EH systems and energy management. In Section 3, we have described the proposed system model and algorithm to estimate optimum energy consumption rate. Section 4 deals with the simulation results and related discussions. Section 5 details conclusion and possible future work. Finally, the paper ends with acknowledgements and references.

2 RELATED WORKS

The authors in (Moser et al., 2010) propose a model for optimizing the energy management of sensor nodes powered from solar energy. The authors opted for an offline multi-parametric programming to compute the application parameters and have also presented a software design comprising a worst-case prediction of the incoming energy. The authors evaluated the designed framework for upper control layer that prevents the sensor nodes from running out of energy as well as for the lower layer, which ensures minimal energy loss.

Another energy management framework based on solar energy harvesting has been proposed in (Castagnetti et al., 2012). The framework is used to simulate an energy harvesting sensor node based on power consumption and energy harvesting, taking into account *energy-neutral* and *negative-energy* conditions. The framework describes a generic energy harvesting system comprising charge consumption rate and energy availability as its parameters along with two energy management architectures, namely - online duty-cycle adaptation and closed-loop power manager.

The definition of WSN lifetime differs depending on the type of application, main function and topology of network (Mansourkiaie et al., 2017). In some works (Chen et al., 2013, Najimi et al., 2014), network lifetime is specified as the instant at which certain number of nodes run out of their stored energy, in (Salarian et al., 2014) the lifetime of the node consuming highest energy is considered as the network's lifetime, while the duration for which the first node in a network is depleted of energy is taken as the network's lifetime in (Jung and Weitnauer, 2013).

The work in (Mansourkiaie et al., 2017) presents a framework to maximize the lifetime of WSNs for structural health monitoring with and without energy harvesting. F. Mansourkiaie *et al* proposed an optimization technique for transmission power level and route selection for each sensor node based on *Branch-and-Bound* and *Genetic Algorithms*. The authors also compared their algorithm with the existing routing algorithms.

In (Akbas et al., 2016) the authors describe a joint optimization framework for transmission power level and packet size to maximize WSN lifetime. The work highlights the joint impact of the packet size and transmission power levels on the network lifetime and also suggests an optimal packet size for each specific scenario where the network lifetime is higher than other packet sizes.

A. Kansal *et al* in (Kansal et al., 2007) present an EH system model based on ENO. The authors also incorporated energy storage parameters in the model and evaluated the experimental results with the theoretical optimal values. Solar powered systems utilizing conservative duty cycle were used to compare the performance of the designed system with other approaches.

3 SYSTEM MODEL

Based on the EH system model described in (Kansal et al., 2007), we propose a system model for RF powered WSNs encompassing ENO and buffer requirements. The model assumes average source energy emission and load energy consumption rate to be P_S and P_L respectively. We further assume that the energy rates vary between two extremities: P_{Smax} and P_{Smin} for source emission, likewise P_{Lmax} and P_{Lmin} for load consumption, where *max* and *min* represent maximum and minimum rates respectively, such that

$$P_{Smax} = P_S + \sigma P_S \text{ and } P_{Smin} = P_S - \sigma P_S \quad (1)$$

$$P_{Lmax} = P_L + \rho P_L \text{ and } P_{Lmin} = P_L - \rho P_L \quad (2)$$

where, σ and ρ is the variation factors defined in the interval $0 \leq \sigma \leq 1$ and $0 \leq \rho \leq 1$.

So, assuming an ideal buffer with zero leakage loss and capacity B, the two worst case conditions for a given time interval T can be states as:

$$B_0 + \eta_{int} A(d,f,x) P_{Smin} T - P_{Lmax} T \geq 0 \quad (3)$$

$$B_0 + \eta_{int} A(d,f,x) P_{Smax} T - P_{Lmin} T \leq B \quad (4)$$

where B_0 is the initial energy stored in the buffer, η_{int} is the overall harvester efficiency and $A(d,f,x)$ represents the path-loss dependent on source-harvester separation (*d*), source frequency (*f*) and ambient condition (*x*).For the above stated conditions, former ensures energy neutrality while the later accommodates the additional constraint to be satisfied for the energy buffer size.

Considering the limiting conditions and setting T so as to ensure ENO for worst case scenarios, we get,

$$\frac{\eta_{int} A(d,f,x) P_{Smax} - P_{Lmin}}{P_{Lmax} - \eta_{int} A(d,f,x) P_{Smin}} = \frac{B - B0}{B0} \quad (5)$$

Equation (5) gives the optimum load consumption rate for any given P_S, considering the buffer capacity is always greater or at worst equal to the initial stored energy, i.e. $B \geq B_0$. This leads to,

$$R = \frac{B - B0}{B0} \geq 0 \quad (6)$$

where R can be defined as buffer ratio, which gives the measure of buffer capacity.

Algorithm 1: Optimum Values for P_{Lmax} and P_{Lmin}.

Input: P_{Smax}, P_{Smin}, η_{int}, $A(d,f,x)$
Output: Optimum values for P_{Lmax} and P_{Lmin}
$P_{Lmax} = 0$
$k = 0$
while $P_{Lmax} \leq \eta_{int} A(d,f,x) P_{Smax}$
for $P_{Lmin} = 0$ to P_{Lmax}
if $\frac{\eta_{int} A(d,f,x) P_{Smax} - P_{Lmin}}{P_{Lmax} - \eta_{int} A(d,f,x) P_{Smin}} \geq 0$
$P_L\_minimum(k) = P_{Lmin}$
$P_L\_maximum(k) = P_{Lmax}$
increment k
end if
end for
increment P_{Lmax}
end while
P_L_small = smallest element among $P_L\_maximum(k)$
P_L_large = largest element among $P_L\_minimum(k)$
for $i = 0$ to k
$D\_max(i) = P_L\_maximum(i) - P_L\_small$
$D\_min(i) = P_L\_minimum(i) - P_L\_large$
$D\_sum(i) = D\_max(i) + D\_min(i)$
end for
ind = index of smallest element among $D\_sum(i)$
$P_{Lmax}\_opt = P_L\_maximum(ind)$
$P_{Lmin}\_opt = P_L\_minimum(ind)$

For given parameters, the optimum values of P_{Lmax} and P_{Lmin} can be calculated as shown in Algorithm 1. The algorithm opts for the values from a possible set of energy consumption rates so as to best satisfy both conditions stated in equations (3) and (4). The optimum average energy consumption rate and buffer ratio can be further deduced using the algorithm outputs.

4 SIMULATION RESULTS AND DISCUSSIONS

In this section, we analyse the optimum values of load energy consumption rate for various source energy rates along with corresponding buffer ratios through simulations in MATLAB. The simulation parameters are listed in Table 1.

The harvester efficiency does not vary significantly for a small variation in the associated energy levels (Chaour et al., 2017, Visser and Vullers, 2013).

Table 1: MATLAB Simulation Parameters.

Parameter	Value
Source to RF-EH distance	5 m
Source frequency	2.45 GHz
Overall harvester efficiency	0.7
Ambient condition	Free space

For simulations the harvester efficiency is considered to be constant within the range of parameters used. Fig. 2-3 shows the variation of average energy consumption rate (P_L) and buffer ratio (R) with available source power (P_S) for different values of variation factor (σ). The simulations show that for a constant value of σ, P_L increases with the increase in P_S and as σ is increased, P_L tends to increase for same P_S values.

It is also evident from the results that the maximum value of R decreases for higher values of σ, suggesting a need for lower buffer capacity for high variations in source energy rate.

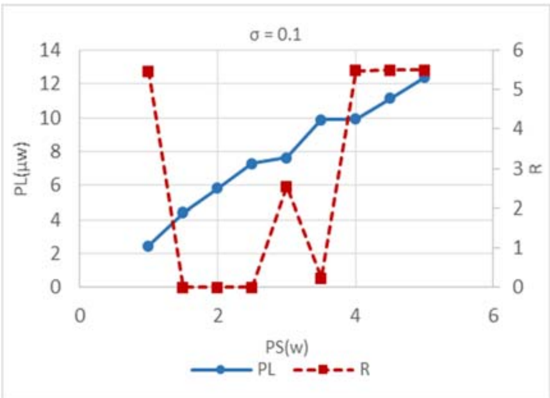

Figure 2: Optimal energy consumption rate and buffer ratio against average source energy rate with variation of 0.1.

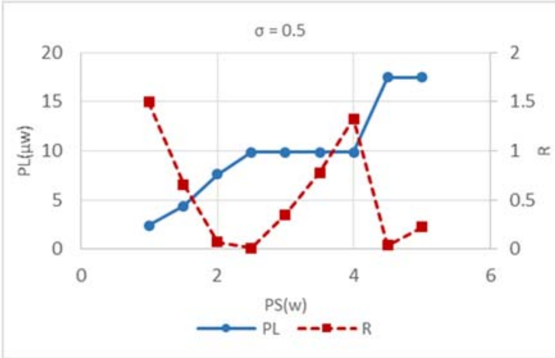

Figure 3: Optimal energy consumption rate and buffer ratio against average source energy rate with variation of 0.5.

The observations also shows that as P_s increases, R decreases, increases or remains unchanged for different rates of change of P_L with P_S. We found that R decreased for higher rates while it remained unchanged for intermediate values and increased for relatively lower rates.

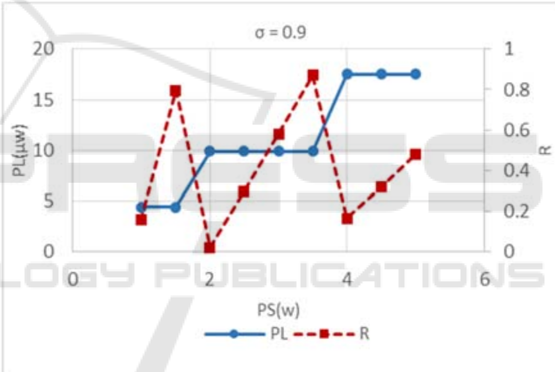

Figure 4: Optimal energy consumption rate and buffer ratio against average source energy rate with variation of 0.9.

The other objective of this work is to evaluate the WSN's lifetime (t_N) for the optimum energy consumption rate obtained from the MATLAB simulations. The measure for t_N is evaluated for a time window T during which the average source energy rate is assumed to be P_S with σ as associated variation factor. To show that the obtained optimum consumption rate provides maximum network's lifetime with minimal buffer capacity, we compare the network lifetimes and buffer capacities for other consumption rates considering energy neutral conditions as described by system model in Section 3. For this, we assume network's lifetime as the duration for which the first node of a WSN depletes its energy. We consider a multi-hop WSN scenario in NS-2.35 with parameters as shown in Table 2 and analyse the network's lifetime for different values of energy consumption rates.

Table 2: NS-2.35 Simulation Parameters.

Parameter	Value
Channel Type	Wireless
Propagation Model	Two-Ray Ground
MAC Type	802.11
Antenna Type	Omnidirectional
Routing Protocol	DSDV
Traffic	TCP (FTP)
Simulation Time	100s

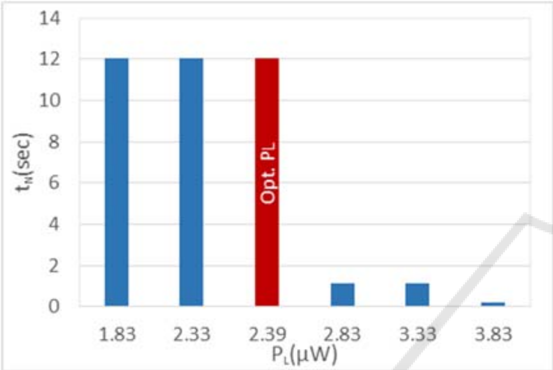

Figure 5: Network lifetime for different values of energy consumption rates (optimal rate marked as Opt. PL).

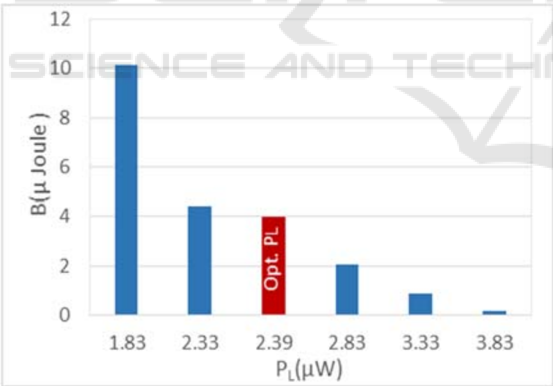

Figure 6: Buffer capacity for different values of energy consumption rates (optimal rate marked as Opt. PL).

Figure 5 and 6 depict the network lifetime and buffer capacity respectively for different values of load energy consumption rate. It is evident from the figure that the WSN lifetime, as compared to the optimum rate, is almost same for lower consumption rates while dramatically shorter for higher rates. From the simulations we also found that for the lower values of consumption rate the increase in lifetime was minimal but the corresponding buffer sizes were

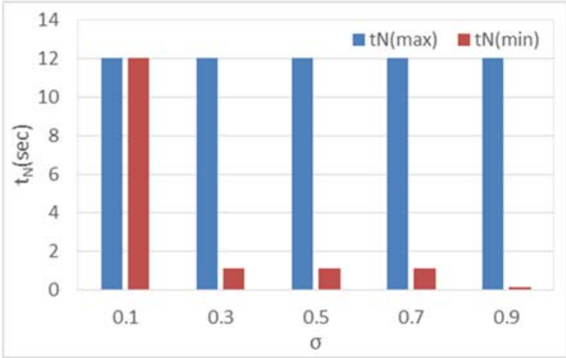

Figure 7: Maximum and minimum lifetimes of sensor nodes with optimal energy consumption rate exposed to different source energy variation levels.

much larger, up to 180%, than the buffer size for the optimum energy consumption rate. On the other hand, though the buffer sizes for consumption rates higher than the optimum rate are lower by 50% to 90%, the network lifetime is reduced greatly by 95%. Hence, the observation indicates that for optimum energy consumption rate a higher WSN lifetime can be achieved for a relatively lower value of buffer capacity.

We also analysed the lifetimes of individual sensor nodes with optimum energy consumption rate for different values of average source energy variation factor. Figure 7 illustrates that for minimum variation of 0.1, the maximum and minimum lifetimes are same, however for higher variations, the difference between maximum and minimum lifetimes tends to increase.

5 CONCLUSION AND FUTURE WORK

In this paper, we have presented a model for RF powered WSN considering energy neutrality and minimum energy wastage. Based on the model, we developed an algorithm that opts for the optimal energy consumption rate and buffer capacity based on worst cases scenarios. Further, we analysed the simultaneous changes in consumption rate and buffer capacity due to change in source energy rate, ensuring continuous energy supply to the load and minimizing energy wastage. We also evaluated the lifetime and buffer capacity of the WSN for optimum load energy consumption rate. The results showed that for the obtained optimum energy consumption rate the network's lifetime is relatively higher for a smaller buffer size as compared to other non-optimal rates.

Finally, we performed a comparative analysis to find the effect of source energy fluctuation in the individual sensor nodes' lifetime.

One of the possible avenues of future work includes designing of energy management system for RF powered WSNs. As for a given energy harvesting rate a corresponding optimal energy consumption rate can be obtained, which can be implemented in a power management module to dynamically adjust individual node's energy consumption rate.

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