Harvesting Aware Power Management for Sensor Networks

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ABSTRACT

Energy harvesting offers a promising alternative to solve the sustainability limitations arising from battery size constraints in sensor networks. Several considerations in using an environmental energy source are fundamentally different from using batteries. Rather than a limit on the total energy, harvesting transducers impose a limit on the instantaneous power available. Further, environmental energy availability is often highly variable and a deterministic metric such as residual battery capacity is not available to characterize the energy source. The different nodes in a sensor network may also have different energy harvesting opportunities. Since the same end-user performance may be achieved using different workload allocations at multiple nodes, it is important to adapt the workload allocation to the spatio-temporal energy availability profile in order to enable energy-neutral operation of the network. This paper describes power management techniques for such energy harvesting sensor networks. Platform design considerations as well as power scaling techniques at the node-level and network-level are described.

Categories and Subject Descriptors

C.2.4 [**Computer Systems Organization**]: Computer Communication Networks—*Distributed Systems*

Keywords

energy harvesting, power scaling, Heliomote

1. INTRODUCTION

Despite significant research effort, energy consumption continues to remain a key challenge during the design of battery-powered electronic systems [8]. In emerging application domains such as wireless sensor networks, the problem is particularly severe due to extra-stringent constraints on cost, form factor, and desired system lifetime.

While power management techniques optimize the *consumption* of energy by the system, a complementary approach is to augment the energy *supply* of the system by harvesting additional energy from the environment at runtime. Due to their physically embedded nature, sensor networks are especially well-suited to exploit ambient energy sources often present in abundance. While numerous harvesting modalities have been demonstrated (*e.g.*, solar,

vibrational, biochemical, motion based, *etc.*), which provide the ability to extract energy from the environment, they must be efficiently integrated into the design and operation of the sensor network to translate the harvested energy into increased application performance and system lifetime.

Compared to a battery-powered system, the power management considerations for an energy harvesting sensor network change, both at the node level and at the network level. First, due to the inherent variability present in environmental energy sources, modeling the energy availability itself is significantly more involved than a simple description of the residual battery energy at all nodes. Second, conventional energy optimization metrics no longer hold in an energy harvesting scenario. For instance, a commonly used objective in battery-powered sensor networks is to maximize network lifetime under a total energy constraint. Clearly, this is not applicable if energy harvesting is allowed since the amount of energy available itself depends on the time duration for which the system operates. Instead, a more relevant design objective might be to maximize the performance of the network while operating in an energy-neutral manner to ensure near-perpetual lifetime. Achieving this requires new harvesting-aware power management techniques that balance the sensor network's load by matching the spatio-temporal energy consumption profile of the network to the corresponding environmental energy availability profile.

1.1 Paper Overview

This paper addresses the issue of power management for energy harvesting sensor networks. We first discuss hardware design considerations for energy harvesting modules, including strategies for efficiently extracting, storing, and using energy from harvesting transducers as well as features required for supporting harvesting-aware power management. Next, we describe a high-level model for characterizing time-varying environmental energy sources and use it to analyze the conditions under which energy-neutral operation of a node can be guaranteed. Based on this, we describe harvesting-aware power management techniques for a single sensor node that explicitly consider the temporal dynamics of the energy source and the non-ideal characteristics of energy storage elements. Finally, we discuss power management methods for a network of harvesting enabled nodes. In addition to node-level issues, these methods also account for the spatial variation in harvesting opportunity across nodes and the relationship between global network performance and the energy consumed by individual nodes.

2. DESIGNING HARVESTING SYSTEMS

This section discusses the various considerations and tradeoffs involved in the design of an energy harvesting module. While our discussion is tailored towards solar harvesting, these design considerations hold for other harvesting modalities as well.

The two primary design goals for any harvesting module are extreme energy efficiency and high reliability. Constraints on form-
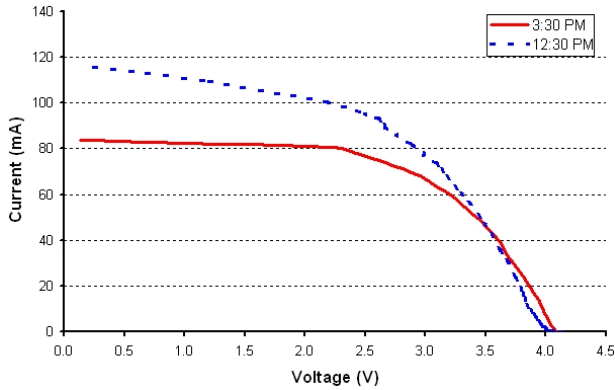
Figure 1: Measured I-V characteristics of the Solar World 4-4.0-100 solar panel at two different times of the day.

factor and cost, as well as limitations in the underlying harvesting technology (*e.g.,* low cost solar panels have a conversion efficiency of around 5%), result in very little energy output from the transducer. In order to make as much of this energy available to the load as possible, it is paramount for the harvesting module itself to be ultra energy efficient. Reliability is crucial since we are designing the power supply sub-system, which is the lifeline of the entire embedded system. Any error or mis-configuration in the harvesting module can cut off power to the load or worse, permanently damage it, rendering the system completely unusable.

2.1 Maximizing energy conversion efficiency

Solar energy is harvested using transducers (commonly referred to as solar cells) that operate based on the photovoltaic effect to supply electrical power to an attached load. As a power source, solar cells behave very differently from batteries. The measured I-V curve of the 4-4.0-100 solar panel from Solar World [11] is shown in Figure 2.1. It is clear that unlike batteries, solar panels behave as voltage-limited current sources with the operating point (*i.e.,* output voltage and current) determined by the electrical impedance imposed by the load. Also, as marked in the figure, there is an operating point on the I-V curve where maximum instantaneous power is delivered by the solar panel. To maximize the total energy output over the course of the system's lifetime, the panel should be operated *as close as possible* to this maximal power point (MPP) *for as long as possible*. However, this is not simple to achieve since the MPP depends on several time-varying parameters such as solar irradiance, panel temperature, *etc*.

A commonly used technique to ensure MPP operation is to isolate the load (*i.e.,* sensor node) from the solar panel using a switching regulator. The switching characteristics of the regulator determine the effective impedance seen by the panel and hence, the operating point on the I-V curve. Since the regulator's characteristics can be software-controlled, the system can track the MPP as it changes using a perturb-and-observe approach. However, the energy benefits of MPP tracking using this method might be offset by the energy consumed by the extra tracking circuitry itself. An alternative approach used in the Heliomote [7] solar harvesting module is to clamp the outputs of the panel to a secondary battery, which fixes the panel's operating point. The authors demonstrate that, by carefully choosing the panel and battery, *near-MPP* operation can be obtained. Although sub-optimal from an MPP tracking point of view, this approach is attractive since it is virtually overhead free.

2.2 Reducing wastage during energy storage

The energy harvested from the solar panel can be stored in either

batteries or electrochemical double layer capacitors (also known as ultracapacitors). Batteries have a higher energy density and lower leakage, while ultracapacitors have a higher round trip efficiency and offer higher endurance in terms of charge-discharge cycles. While an energy storage hierarchy using an ultracapacitor and a battery is possible [2], the tradeoff is a decrease in efficiency due to the increased complexity/overhead of energy storage management.

The choice of battery also involves several tradeoffs. Li+ based batteries are more efficient than NiMH and have a lower self-discharge rate. However, they also require a more complicated charging circuit. Another important consideration is battery cycle-life. For example, NiMH batteries last for about 500 cycles when subjected to repeated 100% discharge. However, battery endurance increases exponentially as the depth of discharge (DoD) decreases. A battery that is cycled at 10% DoD will last for over 5000 cycles before it reaches end-of-life [6]. Therefore, the energy harvesting module should try to enforce shallow charge-discharge cycles to preserve battery endurance. Finally, since the amount of power generated by the solar panel is very limited, the round trip efficiency of the battery becomes crucial. System-level workload scheduling strategies that eliminate the round trip to the battery by utilizing solar energy directly from the panel significantly reduce energy wastage. Several other battery-related factors, which play a crucial role due to the nature of the target system/application are described in [7].

2.3 Measurement and control circuitry

The control circuitry in the harvesting module oversees the operation of the solar panels, manages energy storage, and routes power to the sensor node. There are several requirements that this circuitry should satisfy. First, the harvesting module should have inbuilt energy measurement capabilities to monitor the terminal voltage and supply current of the solar panel as well as the battery. Further, the sensor node should be able to query the harvesting module for the instantaneous voltage and power values. This enables the sensor node to learn the solar power availability pattern, and build and train a power macro-model that provides information about future power arrival. We will see in the next section how the sensor node can use such models to drive its power management policies.

A crucial aspect is the degree of control that the attached sensor node has over the various settings of the harvesting module. Allowing a sensor node to change the harvesting module's settings at run-time amounts to placing the sensor node in charge of its own power supply subsystem, which is dangerous from a reliability point of view. Instead, it is advisable to use dedicated hardware to implement the control, which would make the harvesting module operate autonomously without any support (or chance of mis-configuration) from the sensor node and also more energy efficient.

The harvesting module should have good power supply filtering especially if switching regulators are used for MPP tracking, since these cause a significant amount of load ripple and may affect the operation of the analog and radio frequency circuitry of the sensor node. Finally, since the primary goal is efficiency, the harvesting circuit should be made as application- and system- specific as possible. Building a general harvesting circuit that works with several solar panels and charges multiple types of batteries is a poor design decision because of the efficiency loss that inevitably accompanies such a general purpose solution.

3. SINGLE NODE POWER MANAGEMENT

A key consideration that affects power management in an energy harvesting node is that instead of minimizing the energy consumption, the lifetime may be maximized by operating in an *energy neutral* mode: consuming only as much energy as harvested. This

strategy can enable an indefinitely long lifetime, limited only by the hardware longevity. Reducing the power consumption below energy neutrality will not increase the lifetime further.

3.1 Harvesting Theory

We develop the following theory to develop a fundamental understanding of the energy neutral mode. Let $P_s(t)$ denote the harvested source power output at time t and $P_c(t)$ denote the power consumption. To model the energy buffer, we consider the two parameters typically used for batteries: storage efficiency, η, and a constant leakage current ρ_{leak}. The condition for energy neutrality may be expressed as:

$$\eta \int_0^T [P_s(t) - P_c(t)]^+ dt - \int_0^T [P_c(t) - P_s(t)]^+ dt$$
$$- \int_0^T \rho_{leak} dt + B_0 \geq 0 \quad \forall T \in [0, \infty) \qquad (1)$$

where B_0 is the energy stored of the energy buffer at time $t = 0$ and the function $[x]^+ = x$ if $x > 0$ and is zero otherwise. In modeling loss due to battery inefficiency, we have considered the worst case scenario: energy production times are completely non-overlapping with the consumption times and this causes all the harvested energy to be first stored in the buffer and then used. This explains the multiplication by η for the times when $P_s(t) > P_c(t)$.

The following general model for a energy harvesting source was developed in our prior work [4]:

DEFINITION 3.1 ($(\rho, \sigma_1, \sigma_2)$ FUNCTION:). *A non-negative, continuous and bounded function $P(t)$ is said to be a $(\rho, \sigma_1, \sigma_2)$ function if and only if for any value of positive and finite positive real numbers τ and T, the following are satisfied:*

$$\int_\tau^{\tau+T} P(t)dt \leq \rho T + \sigma_1 \qquad (2)$$
$$\int_\tau^{\tau+T} P(t)dt \geq \rho T - \sigma_2 \qquad (3)$$

For instance, using t for time, if the harvested energy profile $P_s(t)$ is a $(\rho_1, \sigma_1, \sigma_2)$ function, then the average rate at which energy is available over long durations becomes ρ_1, and the burstiness is bounded by σ_1 and σ_2. The consumption profile, $P_c(t)$, may be modeled as a (ρ_2, σ_3) function, where the parameters ρ_2 and σ_3 are used in a constraint of the form (2) to place an upper bound on consumption while no constraint is placed on the minimum consumption.

The condition for energy neutrality, equation (1), leads to the following theorem, based on the energy production, consumption, and energy buffer models discussed above.

THEOREM 3.2 (ENERGY NEUTRAL OPERATION). *Consider a harvesting system in which the energy production profile is characterized as a $(\rho_1, \sigma_1, \sigma_2)$ function, the load is characterized by a (ρ_2, σ_3) function, and the energy buffer is characterized by parameters η for storage efficiency, and ρ_{leak} for leakage. The following conditions are sufficient for the system to achieve energy neutrality:*

$$\rho_2 \leq \eta \rho_1 - \rho_{leak} \qquad (4)$$
$$B \geq \eta \sigma_1 + \eta \sigma_2 + \sigma_3 \qquad (5)$$
$$B_0 \geq \eta \sigma_2 + \sigma_3 \qquad (6)$$

where B denotes the capacity of the energy buffer and B_0 is the initial energy stored in the buffer.

The proof is presented in [3].

This theory has two important design implications. First, it specifies the size of the energy buffer required to achieve energy neutrality for given bustiness bounds on energy production and consumption. This size can be directly used in designing the system. Using a larger battery will not yield increase in sustainable performance or lifetime, though it may help make up for errors in learning the model parameters $\rho_1, \rho_2, \sigma_1, \sigma_2$, and σ_3. Second, the above theorem characterizes the sustainable performance level that may be supported in energy neutral mode. This is significant for system design both in hardware and software. At the hardware level, if the sustainable energy consumption supported is unacceptable, changes may be made to increase the harvested energy. In software, this level will help determine the appropriate power scaling required based on the relationship of the energy consumption to system performance.

The above theory used data regarding the energy production and consumption profiles. The buffer size and stored energy levels were also relevant information. Thus, the additional capabilities for energy tracking capabilities and the integrated storage methods discussed in section 2 are essential to power management in harvesting systems.

3.2 Practical Power Scaling Method

We now discuss a power management method to achieve energy neutral operation. This method has three objectives: learn the harvested energy profile, adapt the performance level to the learned harvesting opportunity with tolerance for errors in learning, and further optimize the performance scaling for battery characteristics. The last objective is important because it helps minimize the energy loss due to battery inefficiency.

In the above discussion, ρ_2 referred to the sustained power consumption at the node, with a busrtiness parameter σ_3. A power scaling method must be chosen to adapt the power consumption to the sustainable level. We choose to use duty-cycling between active and low power modes for the purpose of performance scaling. Most current low power devices provide at least one low power mode in which the node is practically inactive and power consumption is negligible. Other performance scaling methods may of course be considered when available.

3.2.1 Energy and Performance Model

Given that we use a duty cycling approach for power scaling, we need to relate the duty cycle, D to the power consumption and to the system performance. We view the system performance in terms of system utility to the user. Suppose the utility, $U(D)$, at a duty cycle D is given as follows:

$$U(D) = 0, \quad \text{if} \quad D < D_{min} \qquad (7)$$
$$U(D) = k_1 D + \alpha \quad \text{if} \quad D_{min} \leq D \leq D_{max} \qquad (8)$$
$$U(D) = k_2 \quad \text{if} \quad D > D_{max} \qquad (9)$$

It is graphically represented in Figure 2. This is a fairly general model and the specific values of D_{min} and D_{max} may be determined as per application requirements. As an example consider a sensor node designed to detect intruders crossing a periphery. The fastest and the slowest speeds of the intruders may be known, leading to a minimum and maximum sensing delay tolerable, and these result in the relevant D_{min} and D_{max} for the sensor node. The energy usage may be related to D as follows. Suppose the time axis is discretized into slots of duration ΔT, and the duty cycle adaptation calculation is carried out over a window of N_w slots. Define discretized versions of the energy profile variables, with the index i ranging over $\{1, .., N_w\}$: $P_s(i)$ – the power input from the harvested source in slot i, P_c – the power consumption of the load,
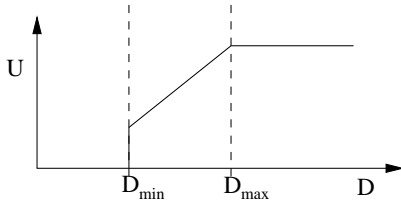
Figure 2: Duty cycle and application utility relationship.

when in active mode[1], $D(i)$ – the duty cycle used in slot i, and $B(i)$ – the residual battery energy at the beginning of slot i. Figure 3 shows two possible cases for $P_s(i)$ in a time slot - it may either be lower than or higher than P_c, as shown on the left and right respectively. When $P_s(i)$ is lower than P_c, some of the energy used comes from the battery, while when $P_s(i)$ is higher than P_c, all the energy used is supplied directly from the harvested source. The crosshatched area shows the energy that is available for storage into the battery while the hashed area shows the energy drawn from the battery. When energy is stored into the battery, some of it is lost due to storage inefficiency.
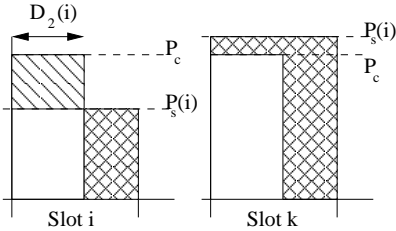
Figure 3: Energy calculation for direct use and with storage.

3.2.2 Performance Maximization Objective

The performance objective is: maximize the average utility over the time window N_w, subject to a minimum duty cycle, D_{min}, desired in any slot and the energy neutrality constraint.

We can write the energy used from the battery in any slot i as:

$$B(i) - B(i+1) = \Delta T D(i)[P_c - P_s(i)]^+ - \eta \Delta T P_s(i)\{1 - D(i)\} - \eta \Delta T D(i)[P_s(i) - P_c]^+$$

In the above equation, the first term on the right hand side measures the energy drawn from the battery when $P_s(i) < P_c$, the next term measures the energy stored into the battery when the node is in sleep mode, and the last term measures the energy stored in active mode if $P_s(i) > P_c$. For energy neutral operation, we require the battery at the end of the window of N_w slots to be greater than or equal to the starting battery. Clearly, battery level will go down when the harvested energy is not available and the system is operated from stored energy. However, the window N_w is judiciously chosen such that over that duration, we expect the system to be energy neutral. For instance, in the case of solar energy harvesting, N_w could be chosen to be a twenty-four hour duration, corresponding to the diurnal cycle in the harvested energy. This is an approximation since an ideal choice of the window size would be infinite, but a finite size must be used for analytical tractability. Further, the battery level cannot be negative at any time.

Stating the above constraints quantitatively, we can express the calculation of the optimal duty cycles as an optimization problem:

$$\max_{D(1)...D(N_w)} \left[\frac{1}{N_w} \sum_{i=1}^{N_w} D(i) \right] \tag{10}$$

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[1]Most low power systems have a sleep mode power consumption several orders of magnitude lower than the active mode and hence a zero sleep mode power is assumed.

$$
\begin{aligned}
B(i) - B(i+1) &= \Delta T D(i)[P_c - P_s(i)]^+ \\
&\quad - \eta \Delta T P_s(i)\{1 - D(i)\} \\
&\quad - \eta \Delta T D(i)[P_s(i) - P_c]^+ \quad \forall i
\end{aligned} \tag{11}
$$

$$B(1) = B_0 \tag{12}$$

$$B(N_w + 1) \geq B_0 \tag{13}$$

$$D(i) \geq D_{min} \quad \forall i$$

where B_0 is the starting residual battery energy and $i \in \{1, ..., N_w\}$. This is a linear optimization problem and while it can be solved using any standard linear programming toolbox, we exploit the structure in the problem to develop a computationally tractable solution for embedded implementation in [1].

3.2.3 Performance Scaling Algorithm

The above optimization uses the harvested power levels in all time slots of the adaptation window. Clearly, these are not known in advance when adapting the duty cycle and hence must be predicted by the power scaling algorithm. Further, the prediction process may have errors and the algorithm must adjust its power scaling decisions to the real time energy measurements.

We use a prediction model based on an Exponentially Weighted Moving-Average (EWMA) filter. The method is designed to exploit the diurnal cycle in solar energy but at the same time adapt to weather and seasonal variations. A historical summary of the energy generation profile is maintained. While the storage data size is limited to a vector length of N_w values in order to minimize the memory overheads of the power management algorithm, the window size is effectively infinite as each value in the history window depends on all the observed data up to that instant. A window size duration is chosen to be 24 hours and each slot is taken to be 30 minutes as the variation in generated power level is assumed to be small within a 30 minute duration. This yields $N_w = 48$. On a typical day, we expect the energy generation to be similar to the energy generation at the same time on the previous days. The value of energy generated in a particular slot is maintained as a weighted average of the energy received in the time-slot at that time of the day during all observed days. The weights are exponential, resulting in decaying weights for older data. Let $x(i)$ denote the value of energy generated in slot i as observed at the end of that slot. Then, the historical average maintained for each slot is given by:

$$\bar{x}(i) = \alpha \bar{x}(i-1) + (1-\alpha)x(i) \tag{14}$$

where α is a weighting factor, and $\bar{x}(i)$ is the historical average value maintained for slot i. Since α is less than 1, the contribution of older values of $x(i)$ becomes progressively smaller. This is referred to as an EWMA filter. Other prediction methods may be employed to suit the energy generation profile. The average value derived for a slot is treated as an estimate of predicted energy value for the slot corresponding to the same slot of the previous day.

The predicted values at the start of a day are used to choose the duty cycles $D(i)$'s for the entire day by solving the optimization problem considered in section 3.2.2. However, since the predicted energy values may deviate significantly from the true energy generation profile on a given day, the duty cycles are adapted in real time to the measured energy values for ensuring energy neutrality.

Denoted the initial duty cycle assignments for each time slot i computed using the predicted energy values as $D(i) = \{1, ..., N_w\}$. First we compute the difference between predicted power level $P_s(i)$ and actual power level observed, $P'_s(i)$ in every slot i. Then, the ex-

cess energy in slot i, denoted by X, can be obtained as follows:

$$X = \begin{cases} \Delta P & \text{if} \quad P'_s(i) > P_c \\ \Delta P - D(i)\Delta P \left(1 - \frac{1}{\eta}\right) & \text{if} \quad P'_s(i) \leq P_c \end{cases}$$

where $\Delta P = P_s(i) - P'_s(i)$. If $\mathbf{X} < \mathbf{0}$, we want to reduce the duty cycles used in the future slots to make up for this energy shortfall. We reduce the duty cycles for time slots whose energy usage is most inefficient, *i.e.*, slots whose harvested energy is the least and most energy comes from the battery. This is accomplished by iteratively reducing the duty cycle to D_{min} in future slots with lowest harvested energy, until the total reduction equals X. If, $\mathbf{X} \geq \mathbf{0}$, we iteratively increase duty cycles to D_{max} in slots which have the most efficiency use of harvested energy.

3.2.4 Evaluation

We evaluated our adaptive duty cycling algorithm based on energy data gathered in a residential area in Los Angeles for a period of 72 days. Based on this data, we compared the performance of our adaptive power management strategy against the optimal approach and a naïve approach in term of their harvested energy utilization. For the optimal approach, we use future energy profile to compute the exact duty cycles that maximize utility, and this gives us a upper bound on the optimal performance. For the naïve approach, duty cycle is kept constant within each window of N_w slots and is computed by taking the ratio of energy stored and active mode energy consumption over a window of N_w slots:

$$D = \frac{\eta}{N_w P_c} \sum_{i=1}^{N_w} P_s(i)$$

We compare the performance of our dynamic duty cycle adaptation algorithm to the two extremes with varying battery efficiency. Figure 4 shows the fraction of solar energy utilized by each of three methods, using $D_{max} = 0.8$ and $D_{min} = 0.3$. The figure shows
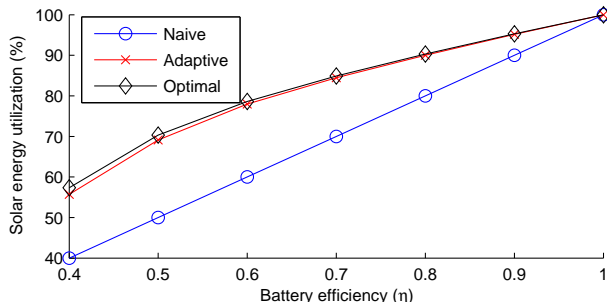
Figure 4: Performance with varying battery efficiency.

that our proposed adaptive algorithm achieves near optimal performance and has significant advantage over a fixed duty cycle approach that does not try to maximize the use of energy in the slots when it is harvested.

4. NETWORK POWER MANAGEMENT

We now consider a distributed network in which some or all the nodes have a harvesting opportunity. The performance potential from an energy environment depends on the spatio-temporal variation in the energy availability across the network. The distribution of this energy in space and time significantly affects the network performance. For instance, if large amounts of energy are available but concentrated only in a small region of the network, the nodes in regions without energy supply will limit the total useful lifetime of the network, beyond which any available energy in other regions may not be useful.

Clearly, each node in the network must achieve energy neutral operation for the entire network to be energy neutral. However, multiple workload allocations among the nodes may yield the same system utility. Hence, it is important to choose a workload allocation that is aligned with the spatio-temporal characteristics of energy harvesting opportunity. For instance, the utility to the user may depend on the amount of data delivered but not on the specific routes used to deliver that data. A harvesting aware power management strategy will use routes which allow maximum data throughput while maintaining energy neutrality.

The performance itself is characterized using application specific metrics. Theoretical abstractions to model energy neutral operation in a network were considered in [3]. Below, we consider the routing application as an example and present a harvesting aware routing scheme which attempts to align the allocation of routing energy consumption with the harvested energy profiles across the network.

4.1 Harvesting Aware Routing

Routing in wireless ad-hoc networks relying on battery power typically uses battery energy based routing cost metrics [10, 9]. The objective is to choose routes in such a way so as not to deplete batteries at certain centrally located nodes which happen to lie along many shortest-hop paths but distribute the routing load uniformly across the network to leverage the total battery resource for maximizing lifetime.

In an energy harvesting network, battery awareness is not sufficient to select the best routes. For instance consider a solar energy harvesting network. Suppose one of the network nodes, node A say, happens to be located under shade at all times and has no solar harvesting opportunity, while a node B has a higher harvesting opportunity. On a given day, if node A has higher battery reserve than B, a battery aware strategy will choose to route through node A while an environment aware strategy may know that the battery at node B has been used more since it has higher harvesting potential and can be used to save energy at node A even when it has a lower battery reserve because node B will likely get replenished.

We thus propose a harvesting energy based cost metric for routing in such networks. Suppose a an environment learning algorithm is available at each node that yields the expected rate of energy harvesting, ρ_i, at node i. Assume a total of N nodes in the network. However, it must be noted that considering harvested energy alone is not enough since certain nodes may not have any harvesting opportunity and hence the battery would have to be depleted at those nodes. Also, it is possible that the network is not operating in an energy neutral mode and the performance desired require more energy to be consumed that harvested from the environment: making the harvested energy a supplement to the battery supply rather than a complete replacement. Additionally, the battery level also helps model the variability in consumption loads among nodes with similar harvesting potential. Thus, we also include the residual battery level B_i at node i in the routing cost metric. Combining these parameters, define an energy potential, E_i, at node i as follows:

$$E_i = w * \rho_i + (1 - w) * B_i \qquad (15)$$

where w is a weight parameter, $0 \leq w \leq 1$ and is typically set close to 1. A low value of w may be relevant in networks powered predominantly by batteries with a small harvesting opportunity. We use the inverse of the energy potential at a node as the communication cost for all links into that node. In other words, in the directed graph representing each node as vertex, v_i and each possible wireless hop between any pair of nodes i and j as an edge e_{ij}, we associate the following cost for each edge into node i:

$$c_{ki}(e_{ki}) = 1/E_i \quad \forall k \in \{k | e_{ki} \in E_{comm}\} \qquad (16)$$

where E_{comm} represents the set of edges across which radio communication is feasible for the deployed network topology and the radio hardware used. Thus, we have a graph representation of the wireless network with each link represented as a weighted directed edge. Several algorithms are available to find the lowest cost routes for given source destination pairs over such a graph, and distributed versions of such algorithms have also been developed. In our prior work, [5], we use a distributed Bellman-Ford method for finding the lowest cost routes. The precise network protocol to learn the harvesting opportunity and exchange the relevant information for finding the environment aware routes is presented in [5]. The fundamental motivation for using such a routing strategy is to align the routing workload allocation with the harvesting opportunity at different nodes.

4.1.1 Evaluation

To evaluate the performance of the proposed routing protocol, light intensity data was collected over a region with vegetation in a forest reserve. Parts of this region are affected by shadows which move with the time of day providing a spatio-temporally varying energy environment for our evaluation. A network of $N = 100$ nodes with equal starting battery reserves was simulated as deployed in this environment with nodes placed randomly such that 50% of them are in regions severely affected by shade and the remaining in sunlit regions for most of the day. Random source destination pairs are generated for the simulation of our proposed routing strategy and a battery aware routing strategy. The time for node deaths is recorded as a performance metric. Figure 5 shows the node death times for the two methods. Clearly, the harvesting aware method increases the useful longevity of the network.
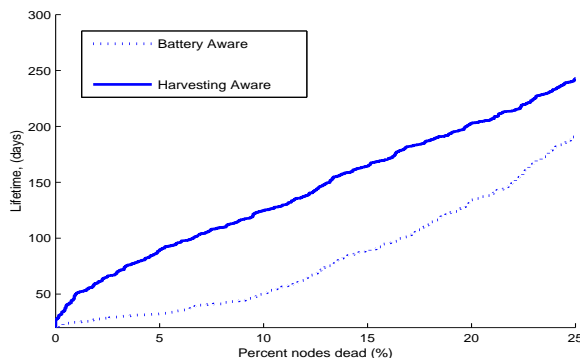

Figure 5: Evaluation of harvesting aware routing strategy.

5. CONCLUSIONS

The emergence of energy harvesting technologies is enabling a viable supplement to battery power in several applications. There are however several issues in efficiently using the harvested energy and providing performance guarantees under highly variable harvested energy output. We developed theoretical abstractions to help model the dynamics of harvested energy in a computationally tractable framework. Our models provided fundamental insights into harvesting system design such as the battery size requirements and sustainable performance levels. We also developed practical power management methods for harvesting systems and showed how these methods can be applied specifically to solar energy. We discussed these methods both for a single device and for a network of harvesting devices.

While energy harvesting has been previously used to supplement battery power, systematic performance guarantees based on a quan-titative characterization of the energy source have not been provided. Our work provides tools to exploit the multitude of emerging harvesting technologies in a performance aware manner. Future research involves applications of our harvesting theory to more sophisticated power scaling methods both for individual nodes and for networks. Interesting research problems also exist in determining appropriate prediction methods for various harvesting modalities other than solar energy and modeling the energy consumption for various applications.

6. ACKNOWLEDGMENTS

7. REFERENCES

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